Final Report on The Use of Fuzzy Set Classification for Pattern Recognition of the Polygraph

R. Benjamin Knapp, PhD

Ulka Agarwal

Ramin Djamschidi

Shahab Layeghi

Mitra Dastamalchi

Eric Jacobs

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1. Introduction

This is the final report of a two year study on the use of fuzzy pattern recognition of polygraph data for the identification of truth versus deception. The goals of this study as stated in the original proposal where to:

1. develop a data parsing algorithm which will process polygraph data obtained from the NSA into three domains: time-domain, frequency domain, and correlation domain;
2. design a fuzzy classifier algorithm to accept the featurized data and modify its membership functions based on the error between its classification of the polygraph data and the classification in the NSA files;
3. study relationship between number of membership functions an the success of the data classification and;
4. investigate the feasibility of the classification being performed in a near-real-time scenario.

The data to be used was MGQT polygraph data. However, the proposal for the second year of the study introduced the goal of comparing the performance of the developed fuzzy classification system with "zone comparison" polygraph data. Ultimately this was changed to be the simulated "relevant only" data obtained from DODPI.

There were two secondary objectives of this project. First, are the features identified as optimal in determining the veracity of a subject optimal for all subjects. Second, are there features not presently being used in polygraph analysis the may be optimal.

This report and its attached appendices will show that all objectives of the original proposal where met. A fuzzy parser and classifier system were developed that could run in near real-time, achieve performances as good or better than the presently available automatic polygraph systems, and identify new features that previously where not used in polygraph classification. Results of 97% correct for the MGQT data and 100% correct for the "relevant only" data were achieved. It will be shown that while certain features yield good identification across all subjects, a clustering algorithm, fuzzy C-means, developed in the second phase of this work identified many sets of features that probably should be tried to achieve optimal performance.

2. Phase I: 1993-1994

The first phase of this project developed a complete automatic data parsing system and fuzzy pattern recognition system based on the fuzzy k nearest neighbor algorithm. These two elements are summarized below.

2.1 Development of Data Parsing Algorithm

The initial goal of this phase was to be able to read the MGQT data files received from the NSA and separate this data into appropriate features for classification. After consulting with the University of Washington, we were able to develop our own data reading program.

After consultation with experienced polygraph examiners and a detailed review of the polygraph literature, the data reading program was then modified to parse the data into a matrix of features. The feature set included, as outlined in the project proposal, time domain, frequency domain, and correlation domain data. Some examples of the feature set are:

<u>Time Domain Features</u>

- Mean, curvelength, area, and standard deviation for all polygraph channels

- Average of the amplitudes of the peaks in the cardio and respiratory channels

- Derivative of the amplitudes of the peaks of cardio and respiratory channels

- Number of peaks in the cardio and respiratory channels

- Inhalation amplitude/exhalation amplitude of respiratory channels

<u>Frequency Domain Features</u>

-Fundamental frequency of cardio and respiratory signals

-Coherency and cross power spectral density between cardio and respiratory channels

-Power spectral density of cardio and respiratory channels

-Integrated power spectral density for cardio channel

<u>Correlation Domain Features</u>

- Autoregressive parameters (10) for cardio signal

- Cross-correlation between cardio and respiratory channels

In order to classify subjects using the difference between control and relevant responses, and to minimize the size of the feature vector, the features were combined according to the following method: for each feature i (except for the three features corresponding to the cross power spectral density and integrated spectral difference) from each subject j compute:

1. The average control responses $AvgCont_{ij}$

2. The average relevant responses $Avg\,\mathrm{Re}\,l_{ij}$

3. The maximum and minimum control responses $MaxCont_{ij} MinCont_{ij}$

4. The maximum and minimum relevant responses $Max\,\mathrm{Re}\,l_{ij} Min\,\mathrm{Re}\,l_{ij}$

The feature vector components for feature *i* are then:

1. $Avg\,\mathrm{Re}\,l_{ij} - AvgCont_{ij}$
2. $\dfrac{Avg\,\mathrm{Re}\,l_{ij} - AvgCont_{ij}}{Avg\,\mathrm{Re}\,l_{ij} + AvgCont_{ij}}$
3. $Max\,\mathrm{Re}\,l_{ij} - MaxCont_{ij}$
4. $Min\,\mathrm{Re}\,l_{ij} - MinCont_{ij}$
5. $Max\,\mathrm{Re}\,l_{ij} - MinCont_{ij}$
6. $Min\,\mathrm{Re}\,l_{ij} - MaxCont_{ij}$
7. $\dfrac{Max\,\mathrm{Re}\,l_{ij}}{MaxCont_{ij}}$

For the three features mentioned previously that cannot be combined as above then from each subject *j* compute:

1. The average of relevant-control responses $Avg(\mathrm{Re}\,lCont)_{ij}$

2. The maximum of relevant-control responses $Max(\mathrm{Re}\,lCont)_{ij}$

3. The minimum of relevant-control responses $Min(\mathrm{Re}\,lCont)_{ij}$

For a complete description of this method, see the report in Appendix B entitled *Feature Analysis of the Polygraph* by Mitra Dastmalchi.

Ultimately 669 features were automatically extracted from the data. The complete list of all 669 features used in this project are shown in Table 1 in the report in Appendix D entitled *Pattern Recognition of the Polygraph Using Fuzzy Set Theory*. The use of this automatic data parsing algorithm is described in more detail in section 4.1.

2.2 Design of Fuzzy Classifier Algorithm

Fuzzy classifier design first focused on the development of a fuzzy set based *k nearest neighbor* algorithm. (This work is described in detail in Appendix C entitled *Pattern Recognition of the Polygraph Using Fuzzy Set Theory* and in *Pattern Recognition of the Polygraph Using Fuzzy Classification,* Proceedings of the 1994 IEEE International Conference on Fuzzy systems, Vol III, pages 1825-1829.) This algorithm is a supervised learning algorithm which means that training data is presented to the algorithm and then the algorithm is "frozen" and test data is presented. **Training on this and all other algorithms in both phases of the study was always performed on 3/4 of the data with testing performed on the remaining 1/4 of the data.** The algorithm learned using a set of MGQT data divided equally between truthful and deceptive. Since there were 150 deceptive files and only 50 truthful files, the deceptive files were divided into three sets of 50 files each. When a question was asked more than once by an examiner the questions were scored individually and then combined at the end on a majority basis. The results of this work are summarized collectively in section 4.2 below.

3. Phase II: 1994-1995

The second phase of this project dealt with creating an unsupervised clustering algorithm which could identify important features more rapidly, creating another supervised learning algorithm to determine if the fuzzy k-NN algorithm was optimal (fuzzy-LMS), creating a genetic search algorithm to try to aid in the search for optimal features, and expanding the algorithm testing to look at simulated "relevant-only" data from DODPI in addition to the MGQT data. These elements are summarized in the two sections below

3.1 Comparison of the Fuzzy C-means, Fuzzy LMS, and Fuzzy k-NN Algorithm

An unsupervised clustering algorithm was created to visualize which features allow for larger separation in the truthful and deceptive data clusters. In addition, a supervised learning algorithm, fuzzy LMS, was created to compare with fuzzy C-means and fuzzy k-NN. (This work is described in much more detail in, and partially excerpted from, Appendix D, *Use of Fuzzy Set Classification for Pattern Recognition of the Polygraph,* and in *Classification of Deception Using Fuzzy Pattern Recognition*, Psychophysiology, Volume 31, Supp.1, August 1994.)

The fuzzy LMS system is unique in its application of linguistic knowledge. The use of linguistic knowledge ensures the robustness of the fuzzy system. The use of linguistic information also ameliorates the problem of not having enough reliable numerical data. Unlike classification schemes such as the K-Nearest Neighbor, the fuzzy LMS algorithm is not entirely dependent on numerical data.

When applied to pattern recognition, fuzzy logic systems can be set up to perform like KNN systems. In KNN systems, numerical data of known class patterns are set up to estimate the probability density distribution of the classes. The probabilities of new data points belonging to the different classes are then computed based on such distribution. Data points around known class samples are then classified into the same class with a higher probability. The fuzzy-KNN algorithm modifies the classical KNN algorithm by taking into account the distance between the data point and the known class patterns when estimating the probability. Conceptually this is similar to setting up clusters around all known class samples and calculating the degree of belonging of new data points in the different types of clusters. Other than the exact mathematical equations, that description fits a fuzzy adaptive system where each rule corresponds to a known class pattern and the size of the clusters is the same for all rules.

However, fuzzy adaptive systems give up some of the nice theoretical understandings of the KNN systems but gain some practical advantages. The number of rules required are usually much smaller than the number of known samples. Fuzzy logic can usually exploit that to reduce system complexity.

Furthermore, the system complexity for a fuzzy adaptive system stays the same even as new information are available. This is partly a result of the way this algorithm adapt continuously; new information are learned as old ones are forgotten. The fuzzy LMS learning technique is like backpropagation, a popular neural network training technique. However, the fuzzy LMS learning algorithm requires few epochs for training. In all our trials the maximum recognition rates for testing data peaked in less than thirty epochs. About 95% of them peaked in less than twenty epochs1. This is a few orders of magnitude less than most applications of backpropagation. In many cases the peaks occurred before any training; that is, the system uses only linguistic rules. Here the use of expert knowledge speeds up the training of the system.

The fuzzy-c-means algorithm, unlike fuzzy LMS, is an unsupervised clustering algorithm. Given a set of data, FCM looks for a (usually) predetermined number of clusters within the data points. It does not use any knowledge about the correct, or desired classification of any of the elements. The algorithm only minimizes an objective function, which is the sum of a function of the data points' membership values and the distances between the data points and the clusters' centers.

FCM operates like a black box; given some data, the algorithm automatically computes the results2. This presents the advantage that different sets of data using different features can be tested in a routine manner. FCM also presents a way to normalize the different dimensions of the data, just like the use of sigma in the fuzzy LMS algorithm. However, unlike fuzzy LMS, FCM does not present a method to find the optimal way for such normalization.

The fuzzy LMS algorithm, however, does pose some potential problems of its own. The use of expert knowledge, while a benefit in some senses, may not be always straightforward. For example, in our project we did not have any specific knowledge about the polygraphy itself. Whatever we learned, we learned by looking at numerical data. As we tried to find more complicated patterns, patterns involving three, four, or more features, the analysis became more difficult. Naturally one wishes to automate this process. If we do not rely on some learning procedures, however, rules cannot be automatically found for the fuzzy system. Much research also needs to be done to understand the fuzzy LMS algorithm's learning dynamics. While the same method, gradient descent, is used on both backpropagation and the fuzzy LMS algorithm, the general shapes of the error surface between the two are different. In backpropagation, all

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[1]However, we ran every trial to forty epochs to ensure that there is no "false" peak.

[2]Our job is basically to adjust the parameters.

the parameters have the same range and lie in an uniform neural network structure. In the fuzzy LMS algorithm, the parameters can have different ranges and lie a fuzzy logic structure that is not completely uniform. The effects of such differences on the shape of the error surface and the learning dynamic are unknown.

A summary of the data comparing these methods is presented in section 4.2 below. All MGQT data was processed as was summarized in section 2.2 above.

3.2 Fuzzy C-means Algorithm on "Relevant Only" Data

The data parsing algorithm was extensively modified to process the relevant only data. This data was composed of 166 truthful and 166 deceptive tests with no irrelevant questions asked. Thus the seven techniques of data combination described in section 2.1 could not be used. Instead, four combinations were used as follows:

1. *Avg(Feature)*
2. *Max(Feature)-Min(Feature)*
3. *Max(Feature) / Min(Feature)*
4. *Std(Feature)*

Also, these files were in an entirely different data format which head to be interpreted for data parsing. (See Appendix E for a summary of incorrect data formats from the "relevant only" data.)

4. Summary of Results

The results for the entire project are summarized below. First, the complete automatic data analysis package is summarized including data parsing and classification. Second, comparison of accuracies amongst the different methods for both MGQT and "relevant only" polygraph data is presented.

4.1 Automatic Data Analysis Method

Below is a description of the automatic data parsing and classification technique developed in this project. Refer to Appendices A-D for a more complete description.

4.1.1 Parsing the Data

4.1.1.1 Reading the Data

It should be noted that the data reading methods are only important for "off-line" processing and would not be used for near real-time applications.

The data was collected in three phases labeled ERS-1, ERS-2 and ERS-3. Each polygraph test may consist of one to five charts with each chart consisting of three files. Each chart is a series of questions, usually ten questions. The files are given in DOS file format and must be read and decoded before they can be seen.

The following files comprise a chart:

$$EACOWO.011

$$EACOWO.021

$$EACOWO.031

Each of these three files has a specific significance. The .XX3 files are text files which contain the questions which the subjects were asked. The .XX1 and .XX2 files are encoded in a specific format created by Axciton polygraph testing devices. These files can be decoded by a program entitled read3. Read3 can be invoked in DOS as in the following example:

read3 $$EACOWO.011 output1

read3 $$EACOWO.021 output2

read3 $$EACOWO.031 output3

The read3 command decodes the data in files X.011, X.021 and X.031 and writes them in ASCII files entitled output1, output2 and output 3, respectively. Output2 and output3 contain the actual signals from four polygraph channels with a timing signal which shows the times when the questions were asked. The output files were labeled such that minimal confusion was allowed. For example, the output file for non-deceptive subject 45, text file .XX3 compiled during phase ERS-1 reads:

nd45t3.ex1

4.1.1.2 Feature Extraction

After the polygraph files are decoded and written into output files, they can be processed in MATLAB. MATLAB is a commercially available mathematical analysis program which runs on a PC, Macintosh, and most UNIX platforms. The feature extraction process consists of a MATLAB program which extracts features for all files and saves them in a matrix consisting of subjects and features. The main feature extraction program is a MATLAB routine called Do.M. This program extracts the pre-selected 52 features, from each subject, contained in the variable feature_list. Feature_list is a MATLAB matrix which includes the names of the feature extraction routines. In each row of the feature_list matrix, a feature extraction routine is named along with the channel number(s) this routine will be applied to. The mean, standard deviation, maximum subtracted from the minimum and the maximum divided by the minimum is taken of the extracted features. These four results are put into a matrix which is then put into a larger matrix called x10.mat, consisting of all non-deceptive and deceptive subjects and all 52 features from the feature list.

4.1.2 Classifying the Data

After the data is parsed in DOS and MATLAB, the classifying process takes place entirely in MATLAB.

4.1.2.1 K-Nearest Neighbor Algorithm

The main program which runs the KNN algorithm is called fknn which is written in the C programming language. This file interacts with MATLAB by reading and writing files in MATLAB format, that is .mat files. This algorithm is implemented by the program fknn which opens a MATLAB data file, reads the training matrix, classifies each entry in the testing matrix and writes the result in an output file. The file from which this program receives information from is "fdatafile.mat" which is in MATLAB file format.

Because the KNN algorithm has been automated, it can be run in only a few simple steps. For a complete description of this process see Appendix C. Before running the algorithm a few variables must be determined. For example, for the "relevant only" data:

1. A single variable 'C', the number of classes was set equal to two for deceptive and non-deceptive.
2. A single variable 'K', determines how many different points surrounding a chosen point will be compared to it and classified. The parameter 'K' in the K-NN algorithm was varied from one to ten throughout the simulations.
3. A single variable 'M', the coefficient in the fuzzy algorithm was set equal to two.
4. A training matrix 'P', contains a set of feature vectors. Each vector is a column of the matrix. There were fifty deceptive and fifty non-deceptive tests used for training. The combination of features to be tested is also entered in this matrix.
5. A class membership matrix 'T', which contains the membership values of the training set vectors to the classes. This matrix was set such that a one was displayed for a non-deceptive detection and a zero for a deceptive detection.
6. An input matrix 'U', which contains a set of unclassified feature vectors contained the rest of the tests not used for training. These remaining tests make up the testing matrix. The same combination of features entered in 'P' are to be entered in the 'U' matrix.
7. Threshold which is varied from 0.2 to 0.8 throughout the simulations.

Once the matrix X10.mat is loaded in MATLAB, the KNN algorithm can be invoked by simply typing "KNN". The user will then be asked to enter a numerical value for the K parameter in the K-NN algorithm. Parameters chosen between one and ten have been found to produce the best results. Once the k parameter has been entered, the number of correct deceptive and non-deceptive detections can be obtained by entering the following:

sum(fresult(1,1:116)>0.5) non-deceptive

sum(fresult(1,117:232)<0.5) deceptive

The correct detection for non-deceptive data is shown by a one, so the threshold is greater than 0.5. The percent correct for the deceptive data can be obtained by dividing the number of correct deceptive detections by 166. This same process works for the non-deceptive data. Finally, the total correct detection percent is obtained by taking the average of the two percentages.

4.1.2.2 Fuzzy C-Means

The Fuzzy C-Means algorithm for MGQT data has been made user friendly through automated push buttons written in MATLAB (see Figure 1). These buttons allow the user to execute the feature extraction and classification process without an understanding of the complexity of each program used in the algorithm. With minor modifications, the push buttons can be used for the "relevant only" data as well.

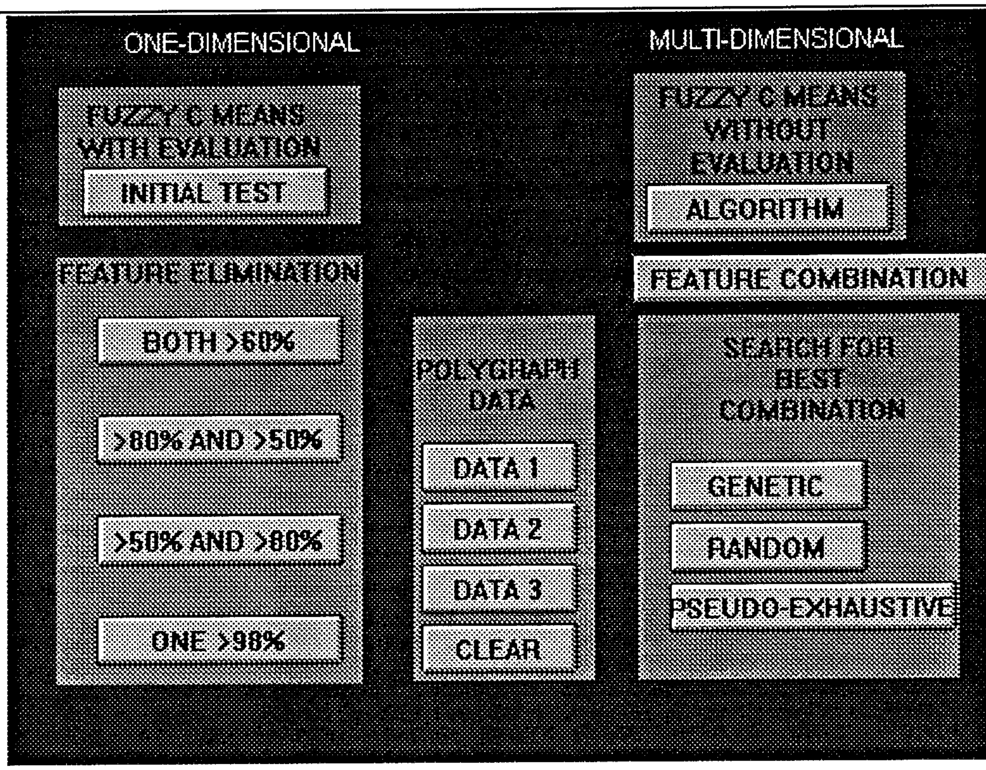

Figure 1: User Interface for Fuzzy C-Means Clustering Algorithm

Before running the algorithm a few variables must be determined. For example, for the "relevant only" data:

1. The 'temp' matrix in the fc_means program was set equal to the dimensions (1,332).
2. The threshold was varied from 0.2 to 0.8 for each different simulation that was run.
3. Combination of features to be tested can be changed as described below.

The following execution process is necessary only if the push button automation is not used. After the matrix X10.mat is loaded, the user must type the following to run the algorithm:

[Uik,z] = fc_means(5,0.000005,x10([8 23 24],:))

The z parameter is the number of iterations made by the algorithm to obtain the results and Uik is the membership values. To calculate the correct detection of non-deceptive and deceptive subjects, the user must type the following:

sum(Uik(1,1:166)<0.5) non-deceptive

sum(Uik(1,117:332)>0.5) deceptive

where 0.5 is the selected threshold for this particular simulation. The percent correct for each class can be determined by dividing the number correct by the total number. The total percent correct is then obtained by averaging the two percentages.

4.1.2.3 Least Mean Squares Algorithm

The LMS fuzzy adaptive filter is a nonlinear adaptive filter which makes use of both linguistic and numerical information concerning the physical characteristics of the polygraph data in their natural form. This filter is constructed from a set of changeable fuzzy IF-THEN rules. We have the choice of setting the rules according to our experiences and incorporating them directly into the filter, or initializing the rules arbitrarily. Before running the algorithm a few variables must be determined. For example, for the "relevant only" data:

1. The number of training subjects was set equal to 100.
2. The 'running time', how often the algorithm goes through the data, was set to 70.
3. Different combinations of the features was changed manually for each different simulation.

After the matrix X10.mat is loaded, the user must simply type:

lmstest.m

The total percent correct of deceptive and non-deceptive data is automatically displayed under the variable 'maximum'.

4.2 Classification Accuracy

4.2.1 MGQT

Figure 2 shows a comparison of the best results for each of the classification algorithms found in this study. (See Appendix D for a more complete description of how this comparison was performed.) It should be noted that the optimum features found for the fuzzy c-means and the fuzzy k-NN algorithms were different. This is important because it means that if both algorithms were run on a given subject, there results could be independent and corroboratory. The fuzzy LMS algorithm was simply run using the optimal four features found for the fuzzy c-means algorithm. The method number refers to the 7 combination methods described in section 2.1 above. The three data files refer to the fact that the 150 deceptive files were separated into three files of 50 and compared to the 50 non-deceptive files.

	Features Used	Data Set 1	Data Set 2	Data Set 3
Fuzzy C-Means	Ampl of Peaks(High Freq Cardio) Meth. 4, Max-Min(High Freq Cardio) Meth. 7, Std(GSR) Meth. 2, Std(GSR) Meth. 4	93	87	97
Fuzzy k-NN	Max(GSR) Meth. 1, Max(Lower Resp) Meth. 6, Max(Upper Resp) Meth. 3, Max-Min(High Freq Cardio) Meth. 4	86	80	91
LMS Fuzzy	Ampl of Peaks(High Freq Cardio) Meth. 4, Max-Min(High Freq Cardio) Meth. 7, Std(GSR) Meth. 2, Std(GSR) Meth. 4	81	83	83

Figure 2: Comparison of Different Classification Techniques of MGQT Data (in percent correct)

4.2.2 "Relevant Only"

For the relevant only data the fuzzy c-means algorithm was used since it achieved the best performance for the MGQT data. Figure 3 shows the summary of results for different combinations of the four optimal features described in Figure 2 above.

Feature(s)	0.2	0.3	0.4	0.5	0.6	0.7	0.8
[2 4]	N: 95	N: 81	N: 64	N: 43	N: 33	N: 20	N: 34
	D: 4	D: 10	D: 28	D: 45	D: 60	D: 78	D: 79
[2 34]	N: 100	N: 96	N: 78	N: 51	N: 11	N: 0.6	N: 3
	D: 0	D: 2	D: 28	D: 58	D: 92	D: 99	D: 97
[2 39]	N: 100	N: 97	N: 83	N: 56	N: 9	N: 3	N: 4
	D: 2	D: 5	D: 29	D: 55	D: 92	D: 97	D: 91
[4 34]	N: 85	N: 52	N: 28	N: 20	N: 11	N: 5	N: 6
	D: 12	D: 41	D: 63	D: 78	D: 84	D: 94	D: 96
[4 39]	N: 84	N: 61	N: 33	N: 21	N: 13	N: 5	N: 4
	D: 10	D: 37	D: 65	D: 72	D: 83	D: 93	D: 92
[34 39]	N: 100	N: 97	N: 90	N: 78	N: 64	N: 36	N: 45
	D: 0.6	D: 3	D: 16	D: 26	D: 40	D: 64	D: 68
[2 4 34]	N: 100	N: 96	N: 78	N: 49	N: 11	N: 0.6	N: 3
	D: 0	D: 3	D: 28	D: 58	D: 93	D: 99	D: 96
[2 4 39]	N: 48	N: 45	N: 36	N: 30	N: 29	N: 24	N: 34
	D: 24	D: 30	D: 32	D: 36	D: 45	D: 48	D: 54
[2 34 39]	N: 48	N: 0	N: 5	N: 33	N: 77	N: 99	N: 100
	D: 24	D: 1	D: 5	D: 32	D: 71	D: 99	D: 100
[4 34 39]	N: 48	N: 45	N: 34	N: 3	N: 22	N: 23	N: 4
	D: 24	D: 30	D: 6	D: 65	D: 54	D: 5	D: 66
[2 4 34 39]	N: 100	N: 99	N: 95	N: 67	N: 23	N: 1	N: 54
	D: 0	D: 0	D: 5	D: 33	D: 71	D: 99	D: 33

Figure 3: Classification of "Relevant Only" Data Using the Fuzzy C-Means Algorithm and Different Combinations of the Four Features Given in Figure 2

Note that for the combination of three features, 2, 34, 39 (which correspond to Std(GSR) Meth. 2, Ampl of Peaks(High Freq Cardio) Meth. 4, Max-Min(High Freq Cardio) Meth. 7) a score of **100% correct for both deceptive and non-deceptive was achieved**.

5. Conclusions

This project achieved all goals set in the phase 1 and phase 2 proposals:

1. a data parsing algorithm was developed which will process polygraph data obtained from the NSA into three domains: time-domain, frequency domain, and correlation domain;
2. several fuzzy classifier algorithms were designed to accept the featurized data and modify its membership functions based on the error between its classification of the polygraph data and the classification in the NSA files;
3. relationships were found between number of membership functions an the success of the data classification up to four simultaneous features;
4. the feasibility of the classification being performed in a near-real-time scenario was shown; and
5. near perfect scores were achieved for both MGQT and "relevant only" data without allowing for any "don't know" results.

Appendix A: Time Domain Features for the Fuzzy Classification of PolyGraph Data

Eric Jacobs

Fall, 1993

Time Domain Features For The Fuzzy Set Classification Of Polygraph Data

EE 297
Dr. Benjamin Knapp
Electrical Engineering Department
San Jose State University

Eric Jacobs
November 1993

Abstract

A polygraph examination is the most popular method used to determine if an individual is being truthful or deceptive. During an examination, a subject is asked a series of questions and the physiological responses to the questions are recorded using a polygraph. The three physical responses currently obtained from a polygraph examinations are blood pressure, respiration, and skin conductivity. Polygraph charts are usually analyzed by a human interpreter for evidence of truth or deception; however, computer algorithms are now being used to verify results [1][2].

In this project, the K nearest neighbor algorithm was used to determine truth or deception. By using this adaptive fuzzy system, it was possible for the computer evaluation of the polygraph to adapt to individual differences in the physiological responses. Two algorithms were necessary for this project. The first was a parsing algorithm which preprocessed polygraph data and extracted features from it. These features can be separated into three domains: time domain, frequency domain, and correlation domain. The second was the K nearest neighbor fuzzy classifier which analyzed the data from the parsing algorithm and determined the possibility of deception.

Contents

1.1 History

The first attempt to use a scientific instrument in an effort to detect deception occurred around 1895 [3]. That was the year that Cesar Lombroso published the results of his experiments in which a hydrosphygmograph was used to measure the blood pressure-pulse changes of criminals in order to determine whether or not they were deceptive. Although the hydrosphygmograph was originally intended to be used for medical purposes, Lombroso found that it worked well for lie detection. Lombroso may have been the first to use a peak of tension test format. This was done by showing a suspect a series of photographs of children, one being the victim of sexual assault. If the suspect did not react more to the victims picture than the pictures of the other children, Lombroso concluded that the suspect did not know what the victim looked like and therefore was not the alleged perpetrator.

In 1914 Vittorio Benussi published his research on predicting deception by measuring recorded respiration tracings [4]. He found that if the length of inspiration were divide by the length of expiration, the ratio would be larger after lying than before lying and also before telling the truth than after telling the truth. In 1921 John A. Larson constructed an instrument capable of simultaneously recording blood pressure pulse and respiration during an examination [3][4]. Larson reported accurate results which prompted Leonarde Keeler to construct a better version of this instrument in 1926 [3][4].

The use of galvanic skin response in lie detection began during the turn of the century. It's usefulness, however, did not become evident until the 1930's during which time several articles written by Father Walter G. Summers of Fordham University in New York [4]. In these articles he reports over 90 criminal cases in which examination using the galvanic skin response had all been successful and confirmed by confession or supplementary evidence. The usefulness of the galvanic skin response prompted Keeler to add an galvanometer to his polygraph. At the time of Keelers death in 1949, the Keeler Polygraph recorded blood pressure-pulse, respiration, and galvanic skin response [3].

1.2 Modern Test Formats

The effectiveness of a polygraph examination is often the result of the test format that is used. A polygraph test format consists of an ordered combination of relevant questions about an issue, control questions that provide a physical response for comparison, and irrelevant questions that also provide a response or the lack of a response for comparison [1][4]. Three general types of test formats are in use today. These are Control Question Tests, Relevant-Irrelevant Tests, and Concealed Knowledge Tests. Each of the general test formats may have a number of more specific variations. Each test consists of two to five charts containing a prescribed series of questions. The test format that is used in an examination is determined by the test objective [3][4].

The concealed knowledge test, also called peak of tension test, is used when facts about a crime are known only by the investigators and not by the public. In this case, a subject would not know the facts unless he or she was guilty of the crime. For example, if a gun was used in a crime and the public did not know the caliber, an examiner could ask a suspect if it was a 22 caliber , a 38 caliber, or a 9mm. If the gun used was a 9mm and the suspect was deceptive, a polygraph chart would probably indicate evidence of deception.

A control question test is often used in criminal investigations. In this type of test a series of relevant, irrelevant, and control questions are asked. A relevant question is one which is specific to the crime being investigated. For example, " Did you molest the child?". A control question is designed to make the subject feel uncomfortable. It is not specific to the crime being investigated however it may be related in an indirect way. A control question that could follow the relevant question stated above is "Have you ever forced yourself on another person sexually ?". The control questions are compared to the relevant questions and if the responses to the relevant questions are greater, the subject is usually classified as deceptive. Irrelevant questions are used as buffers. Examples of irrelevant questions are "Are the lights in this room on?" or "Is today Monday?".

Relevant-Irrelevant tests are usually used to test people trying to obtain security clearance or get a job. In this test, relevant questions are compared to irrelevant questions. Very few control questions are asked. The purpose of control questions in this test is to make sure that the subject is capable of reacting at all.

1.3 Present Day Equipment

The most popular polygraph machines today are the Reid Polygraph developed in 1945 and the Axciton Systems computerized polygraph developed in 1989 [1][11]. The Reid polygraph scrolls a piece of paper under pens that record the biological signals. The Axciton polygraph digitizes physiological signals and uses a computer to process them. The sampling frequency of the Axciton machine is 30 Hz. Axciton provides a computer based system for ranking the subject responses but allows printouts of the charts to be scored by hand the traditional way. The Axciton and Reid polygraphs are shown in figures 1 and 2 respectively.

Both machines record the same biological signals using standard methods. Blood pressure is measured by placing a standard blood pressure cuff on the arm over the brachial artery. Respiration is monitored by placing rubber tubes around the abdominal area and the chest of the subject. This results in two signals, an upper and lower respiratory signal. Skin conductivity is measured by placing electrodes on two fingers of the same hand.

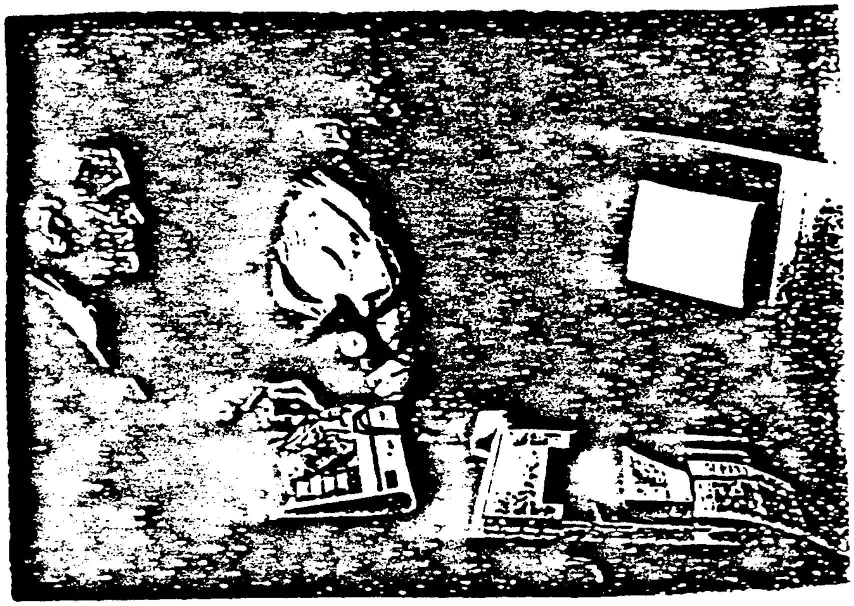

Figure 1   Axciton Polygraph [1]

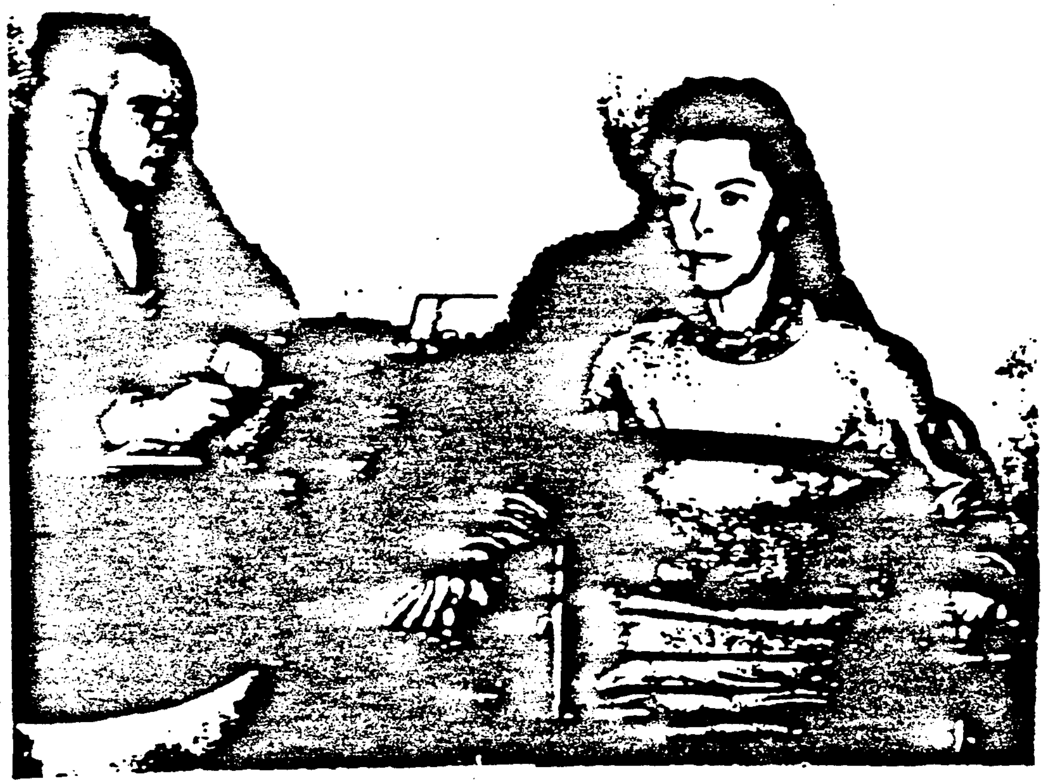

Figure 2   Reid Polygraph [3]

2.1 Fuzzy Set Theory

In 1965 fuzzy sets were introduced by Lofti Zadeh [5][6]. They provided a new way to represent vagueness and made description of many situations much easier. For example, it is not practical to say that all temperatures below 72 degrees Farenheit are cold and all temperatures above are hot. Instead, temperatures between 50 and 72 would by described as cool, temperatures between 30 and 50 would be considered cold, and anything below 30 would be very cold. One way to describe this situation is through the use of fuzzy set theory. In fuzzy set theory an element is not defined as belonging or not belonging to a given set. Instead, it has a degree of membership in a set which is characterized by a compatibility function uA [6] [7]. The compatibility function, also called a membership function, states the degree of membership in a set "A" and has a range [0,1]. An illustration of how this applies to the temperature example above is illustrated in figure 1 and described below.

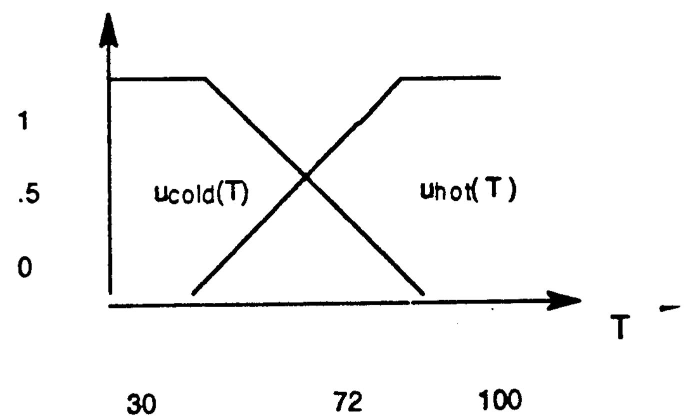

Figure 3 Compatibility functions ucold(T) and uhot(T) vs. temperature.

Here, $u_{cold}(T)$ and $u_{hot}(T)$ are the degrees of membership in each set and T is the temperature in Farenheit. Figure 1 shows that the temperatures around 72 degrees have membership in $u_{cold}(T)$ and $u_{hot}(T)$. These memberships have values around .5 which represents cool or warm. As the cooler temperatures decrease, $u_{cold}(T)$ increases thus representing a colder situation. Once the temperatures become less than 30 degrees, $u_{cold}(T)$ obtains a membership value of 1 which indicates very cold temperatures.

Fuzzy set theory is often thought of as another form of probability theory. In actuality, the two are very different [8]. In Bayesian probability theory, elements either belong or do not belong to a given set, and a probability density function determines the likelihood. For example, a light may be either on or off and the probability of either event occurring will depend on some statistical parameters (Is the room occupied? Is it dark out? etc.). The following is an example of the difference between fuzzy logic and Bayesian probability theory [6].

Example 1

Let L = set of all liquids, and let fuzzy subset l = {all (potable) liquids}. Suppose you had been in the desert for a week without drink and you came upon two bottles marked "C" and "A" as in figure 4a.

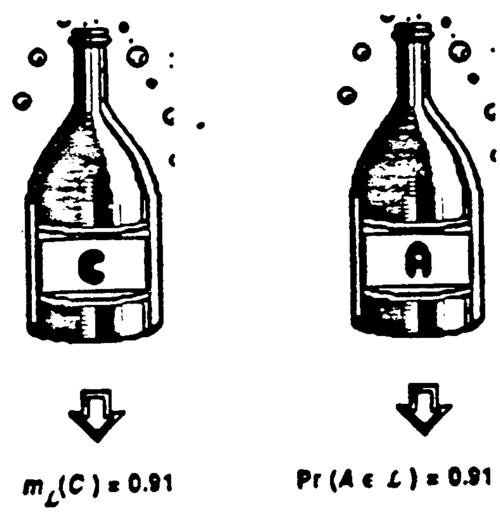

Figure 4a Liquids before observation

Confronted with this pair of bottles, and given that you must drink from the one that you choose, which would you choose to drink from? Most readers, when presented with this experiment, immediately see that while "C" could contain, say, swamp water, it would not (discounting the possibility of a Machiavellian fuzzy modeler) contain liquids such as hydrochloric acid. That is, membership of 0.91 means that the contents of "C" are fairly similar to perfectly potable liquids (e.g., pure water). On the other hand, the probability that " A" is potable = 0.91 means that over a long run of experiments, the contents of A are expected to be potable in about 91% of the trials; in the other 9% the contents will be deadly - about 1 chance in 10. Thus, most subjects will opt for a chance to drink swamp water.

There is another facet to this example, and it concerns the idea of observationion. Continuing then, suppose that we examine the contents of "C" and "A" and discover them to be as shown in figure 4b. Note that, after observation, the membership value for "C" is unchanged while the probability value for A drops from 0.91 to 0.0.

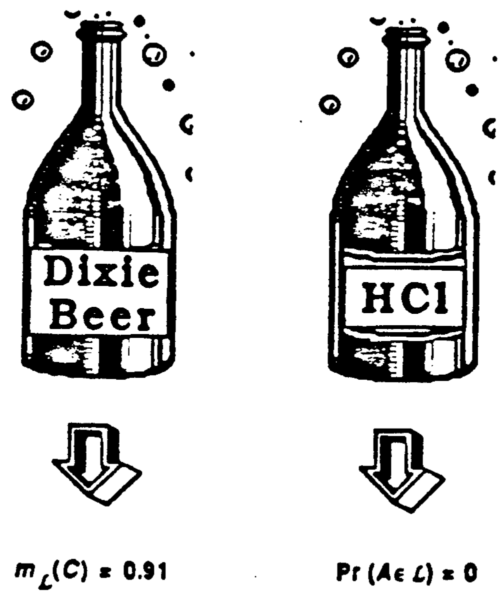

Figure 4b Liquids after observation

This example shows that these two models possess philosophically different kinds of information: fuzzy memberships, which represent similarities of objects to imprecisely defined properties; and probabilities, which convey information about relative frequencies.

3.1 MGQT

The test format used in this project was the MGQT test format. It is a type of control question test in which relevant, irrelevant, and control questions are asked in the order given in table 1 [9][12]. Before each test, the questions that will be asked are discussed with the subject. The series of questions is asked three times in the order specified in table 1. This produces three test charts. The examiner waits about 20 seconds between each question.

Not all of the Axciton charts used in this study follow the format of table 1 exactly. Many examiners rearranged the order in which the questions were asked. All polygraph charts used, however, were variations of this test. For example, one examiner used a test format in which questions 3 and 4 were switched. Many of the examiners changed the order in which the questions were asked in the second and third charts.

Question	Type of Question
1	irrelevant
2	irrelevant
3	relevant
4	irrelevant
5	relevant
6	control
7	irrelevant
8	relevant
9	relevant
10	control

Table 1 MGQT question format

4.1 File Formats

Axciton files, digitized polygraph data from the axciton polygraph, were obtained from the National Security Agency (NSA) in standard MSDOS format. The sampling frequency of the data was 30Hz. Each test consisted of nine files. The labling of the files is shown in table 2 and the purpose of each file is explained below.

Chart 1	Chart 2	Chart 3
$$xxxxxx.011	$$xxxxxx.021	$$xxxxxx.031
$$xxxxxx.012	$$xxxxxx.022	$$xxxxxx.032
$$xxxxxx.013	$$xxxxxx.023	$$xxxxxx.033

Table 2 File format

As stated in the section above, each examination is composed of three charts. The chart number is specified by the second number after the period. The third number after the period represents the type of file.

$$xxxxxx.0x1 is the event marker file which contains the length of the chart and the event markers. The start and end of an examiners question is marked with a 0 and 1, respectively. The beginning of the subjects response is indicated with a 2 and the rest of the file is marked with 9's. File $$xxxxxx.0x2 is the file containing the biological signals. These signals correspond to the marker file. File $$xxxxxx.0x3 contains the questions and labels them relevant, irrelevant, or control.

An ASCII file of five columns is created by using $$xxxxxx.0x1 and $$xxxxxx.0x2 and a program provided by the NSA. An example of this file along with a description of the function of each file is shown in table 3 [12].

	Event Marker	**FileChart Data**	**FileQuestion TextFile**
	$$xxxxxx.0x1	$$xxxxxx.0x2	$$xxxxxx.0x3
Axciton File	Contains the length of the chart, the number of channels, and the position of the event marker.	Contains the digitized series values formatted according to flags in the Event Marker File.	Contains the script of of questions or a shorthand script of questions.
Processing Notes	Becomes the 5th column of ASCII file. 0=start of a question 1=end of a question 2=start of response 9=No Event Marker	Becomes 1st-4th columns of ASCII file. Column 1-GSR Column 2-Cardio Column 3-Upper Resp Column 4-Lower Resp	Files used to determine deviations from standard test format.

ASCII File Format (with column labels)

	File Row	GSR	Cardio	UR	LR	EvMark
DOS File	1	1983	1931	1482	1083	9
	2	1983	1922	1483	1084	9
	3	1983	1913	1483	1084	9
	4	1983	1906	1483	1085	9

Table 3 File description and example

5.1 Preprocessing

MATLAB was used to display the signals and implement all of the filters and feature extraction algorithms. First, the four biological signals were processed into six channels. Hamming windowed FIR filters were used to create these channels and eliminate noise. A low frequency cardiovascular channel was produced by lowpass filtering the cardiovascular signal at .5 Hz using a 134 tap lowpass filter. Then, a high frequency cardiovascular channel was produced by highpass filtering the cardiovascular signal at .5 Hz using a 134 tap highpass filter. The derivative of the low frequency channel was then used to create a third channel. To eliminate noise, the upper and lower respiratory signals were lowpass filtered at 1.2 Hz using a 160 tap filter. Noise was eliminated from the galvanic skin response by using a 100 tap lowpass filter with a cutoff frequency of .5 Hz. Any DC trends that existed within a chart were eliminated using the detrend function in MATLAB. This function finds the best straight line fit to the data and then subtracts the line from the data. Each signal was normalized by dividing by its standard deviation. The raw data and results of this processing are shown in figures 5-14.

Fragments of each signal were accessed before features were extracted. These fragments were successfully used by Brian M. Duston of the Naval Control and Ocean Surveillance Center in his study and are given in table 4 [9]. The start and end points given in table 4 refer to the time elapsed after the question was asked by the examiner.

Channel	Start	End
GSR	2 sec.	14 sec.
Upper respiratory	2 sec.	18 sec.
Lower respiratory	2 sec.	18 sec.
Low frequency cardiovascular	2 sec.	18 sec.
High frequency cardiovascular	3 sec.	9 sec.
Derivative of low frequency cardiovascular	0 sec.	8 sec.

Table 4 Time fragments used in feature extraction

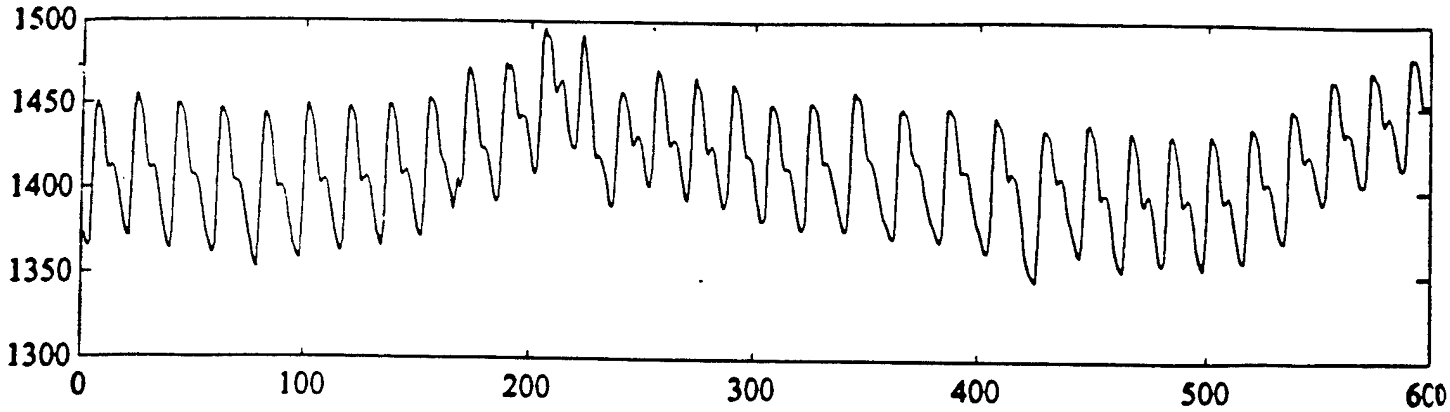

Figure 5 Cardiovascular

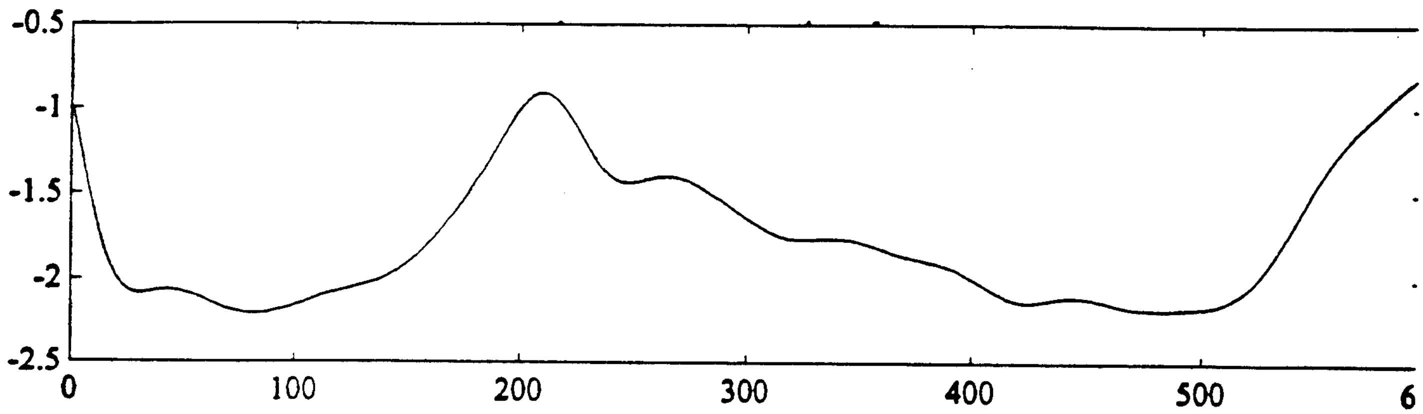

Figure 6 Preprocessed Low Frequency Cardiovascular

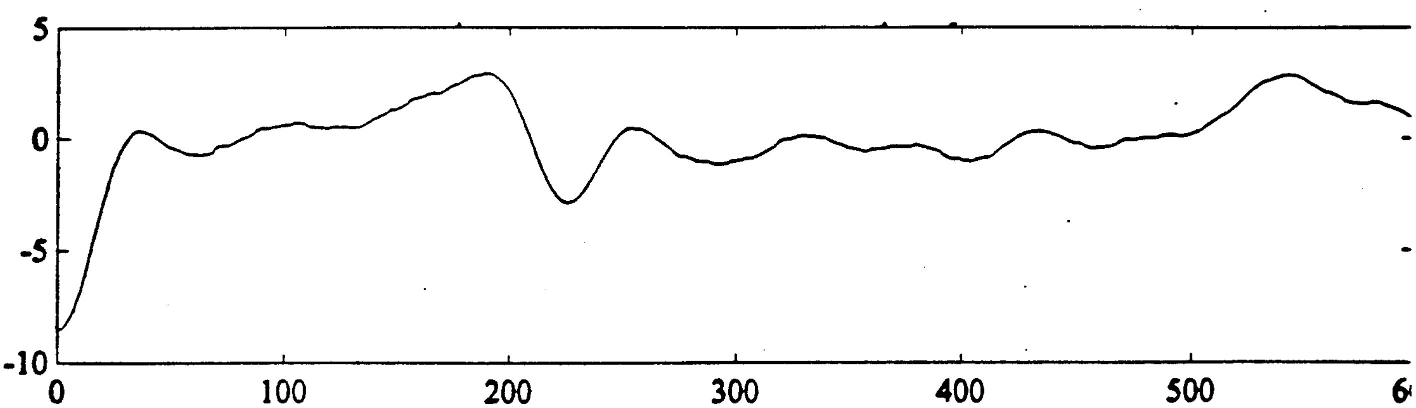

Figure 7 Preprocessed Derivative of Low Frequency Cardiovascular

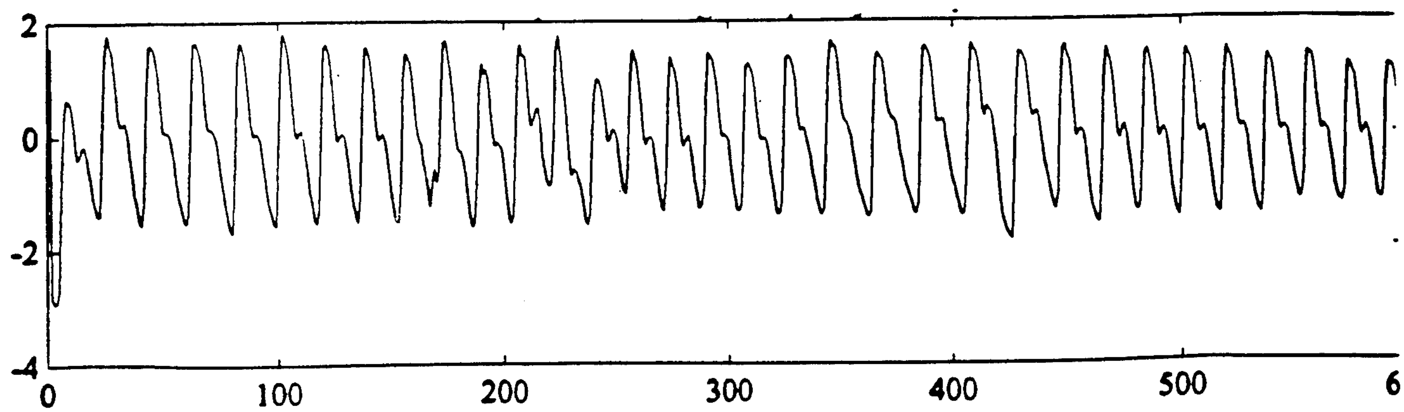

Figure 8 Preprocessed High Frequency Cardiovascular

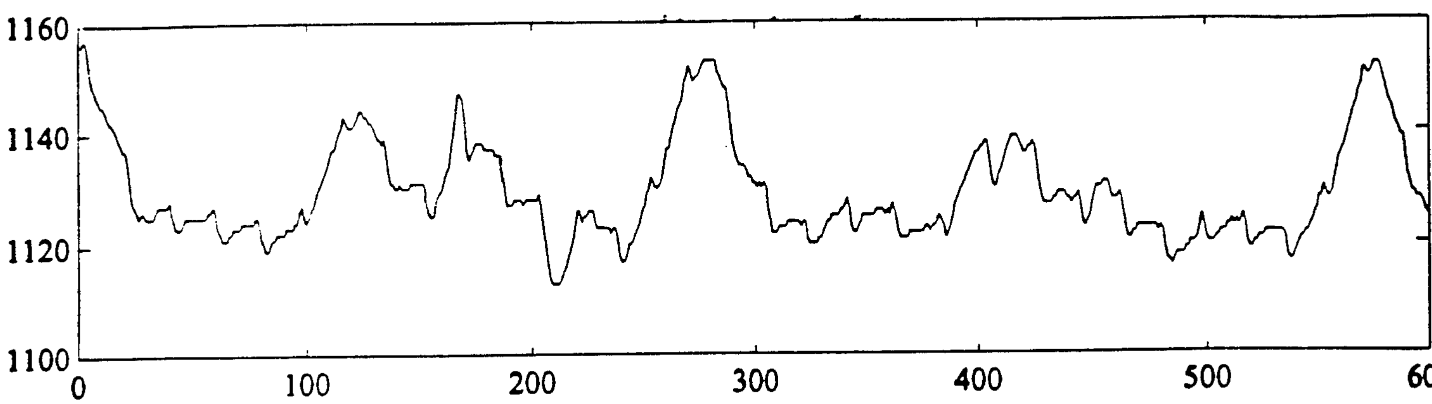

Figure 9 Upper Respiratory

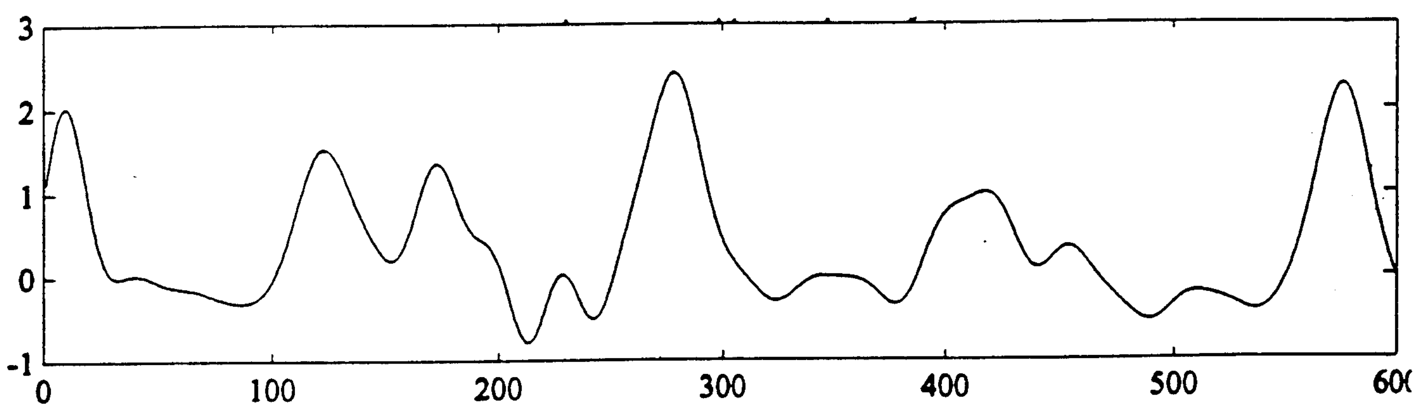

Figure 10 Preprocessed Upper Respiratory

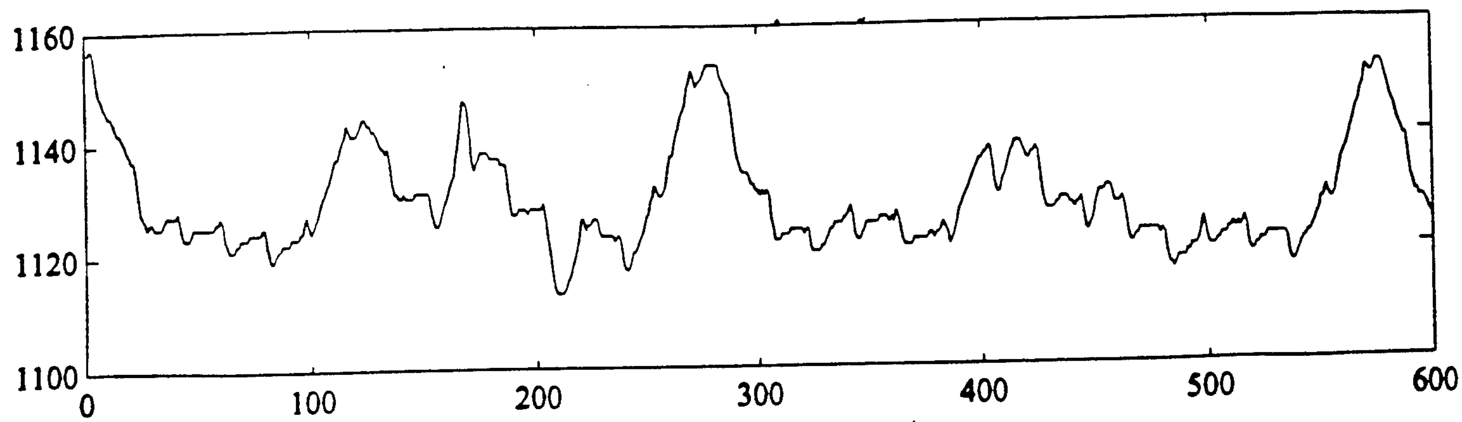

Figure 11 Lower Respiratory

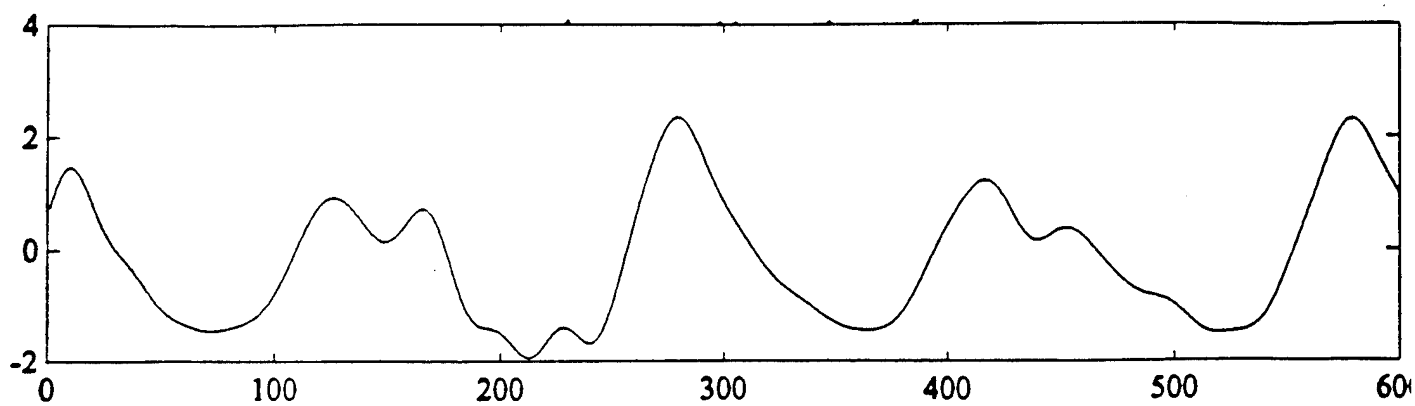

Figure 12 Preprocessed Lower Respiratory

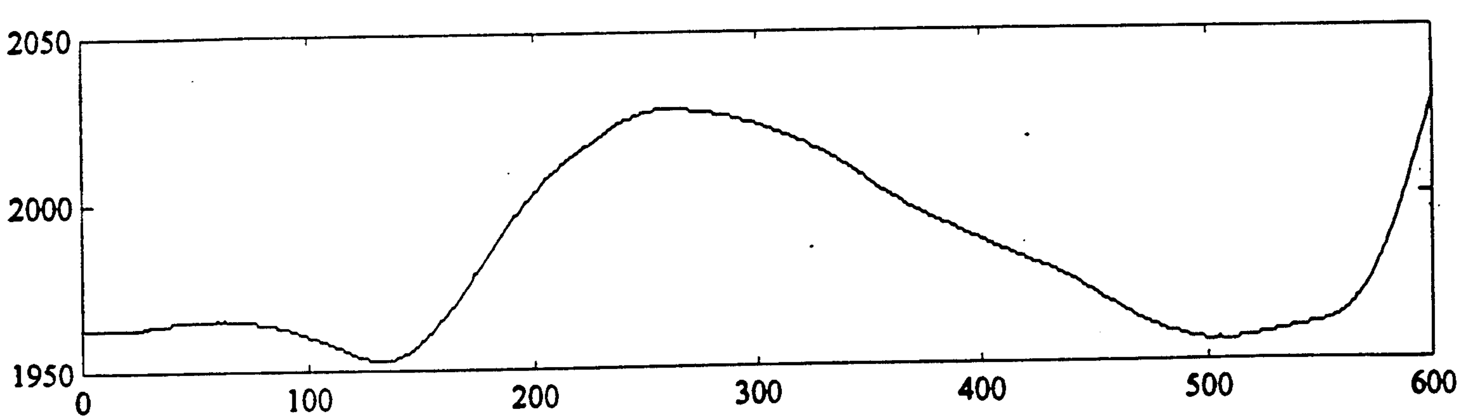

Figure 13 GSR

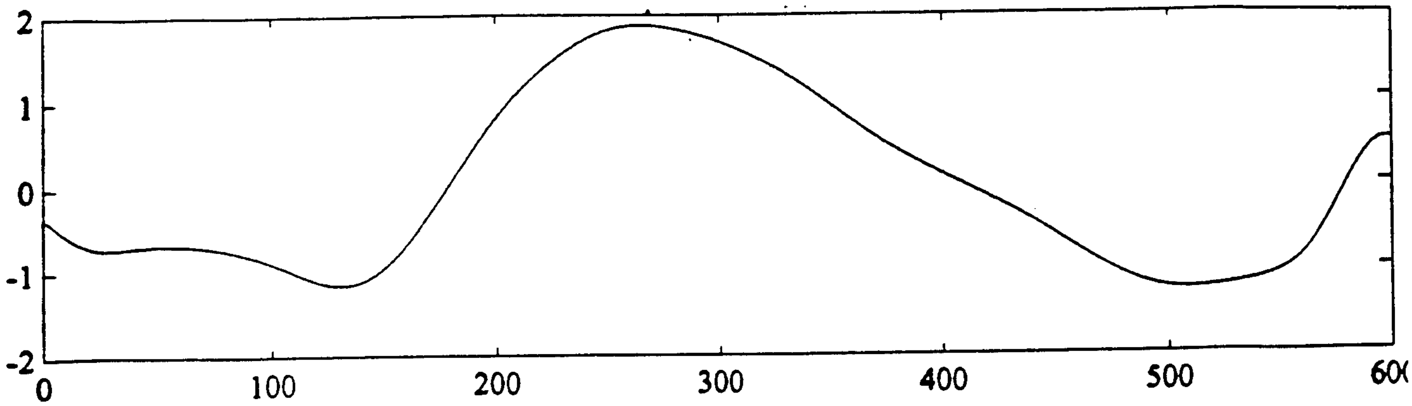

Figure 14 Preprocessed GSR

5.2 Time Domain Feature Extraction

Many of the time domain features were chosen by talking to examiners and finding out what was important to them in an examination [10][11]. One feature examiners use to determine deception involves the height of the peaks in the respiratory signal. If the peaks become smaller or staircase during a relevant question there is a good chance that the subject is being deceptive. From looking at different polygraph charts it could be seen that individual reactions may vary slightly with time. For this reason, many features were extracted from the respiratory channels in order to determine if the deceptive characteristics described above may be present. One feature extracted from the respiratory signal was the average height of the peaks. Because the time fragments from which the features are extracted remain constant, this feature may not give good results for subjects reacting early or late. For this reason, the minimum peak height was also used as a feature.

To try and capture the effect of staircasing, the average of the derivative of the amplitudes of the peaks was used as feature. To compensate for early and late reactions, the maximum of the derivative of the amplitudes of the peaks was also used as a feature.

Another respiratory feature used in this project was the curve length. This feature was successfully used and researched by Howard Timm in the early 1980's[10][13]. Interest in curve length lead to curiosity about the area under the respiratory curve. For this reason it was also extracted to see if it could be used as a feature. Because people tend to breath quicker when they are stressed or nervous, the number of peaks produced during a given period of time was used as a feature.

Because it was one of the first features used to successfully determine deception, Benussi's I/E ratio was tested [3][4]. Benussi's method requires that the I/E ratio of the subject is calculated before and after the examiner asks a question. The value of the I/E ratio calulated after the question is asked is then divided by the value of the I/E ratio before the question is asked. According to Benussi's findings, if the ratio is greater than one, the subject is deceptive. In an attempt to reduce the number of computations required for Benussi's method, a modification of Benussi's feature was tested. In the modification of Benussi's test, the ratio was taken only after the question was asked and was not compared to the subjects I/E ratio before the question was asked.

The examiners we spoke to would usually try to find evidence of deception in respiratory signals first. If a subject did not show a strong respiratory response however, the examiner would analyze the subjects cardiovascular response. Because a subjects heart rate will often increase when deceptive, the number of peaks in the high frequency cardiovascular signal was used as a feature. From looking at many charts, it became evident that some of the processing used in extracting features from the respiratory channels would also be useful in determining deception from the high frequency cardiovascular channel. For this reason, the average of the peak height, minimum of the peak height and curve length were extracted from the high frequency cardiovascular channel in order to determine if they would be useful features.

Many of the standard statistcal features used in other computerized polygraph algorithms were also examined [9]. These features included the mean, the standard deviation, the maximum amplitude, and the minimum amplitude of the signal. Variations of these such as the minimum subtracted from the maximum were also examined. Although the original use of the curve length and area was to determine deception from the respiratory channel, it was extracted from the GSR and cardiovascular channels as well. It was not possible from looking at the signals to determine if the curve length had changed, but almost any change in a signal would affect this feature. A list of the features extracted from each channel are given in table 5. The programs used to extract these features were written in MATLAB and are included in the appendix of this report.

High frequency cardiovascular

1) mean of signal
2) standard deviation of signal
3) minimum value of signal
4) maximum value of signal
5) curve length of signal
6) area under signal
7) average amplitude of peaks
8) minimum amplitude of peaks
9) derivative of the amplitudes of the peaks in the signal
10) number of peaks in the signal
11) minimum subtracted from maximum

GSR

1) mean of signal
2) standard deviation of signal
3) minimum value of signal
4) maximum value of signal
5) curve length of signal
6) area under signal
7) minimum subtracted from maximum

Low frequency cardiovascular

1) mean of signal
2) standard deviation of signal
3) minimum value of signal
4) maximum value of signal
5) curve length of signal
6) area under signal
7) minimum subtracted from maximum

Derivative of low frequency

1) mean of signal
2) standard deviation ofsignal
3) minimum value of signal
4) maximum alue of signal
5) curve length of signal
6) area under signal
7) minimum subtracted from maximum

Upper and lower respiratory

1) mean of signal
2) standard deviation of signal
3) minimum value of signal
4) maximum value of signal
5) curve length of signal
6) area under signal
7) average amplitude of peaks
8) minimum amplitude of peaks
9) derivative of the amplitudes of the peaks in the signal
10) number of peaks in the signal
11) inhalation/exhilation ratio
12) ratio of inhalation ratios before and after a question is asked
13) minimum subtracted from maximum

Table 5 List of time domain features

5.3 Feature Extraction Methods

To extract the following features which are listed in table 5, (respiratory 7, 8,9,10 ,11 and high frequeny cardiovascular 7, 8, 9), it was necessary to locate the peaks of the respiratory and the high frequency cardiovascular signals. This was not a trivial task because these signals contained low amplitude high frequency noise which was difficult to eliminate without distorting the data (see figures 8,10, and 12). In order to find the useful peaks, two programs were written. The program that found the peaks of the respiratory signal was titled peaklr and the program that found the peaks in the cardiovascular signal titled peakcard. Both programs can be found in the appendix. The way that these programs find peaks is as follows: The second derivative was taken and points that had values equal to zero were labeled as peaks. The amplitudes of the signal at points near these peaks were evaluated and the maximum of these values were labeled as peaks.

In order to eliminate the effects of the low amplitude high frequency noise, it was necessary to check the amplitude of data points that were near each point that had been labeled as a peak. The number of the data points from the peaks that were determined by the second derivative was chosen by examining many respiratory and cardiovascular signals and determining the average width of the peaks in these signals. It was found that twenty points on each side of the each peak found by the second derivative was a satisfactory range for the respiratory signals. Similarly eight points on each side of the initial peak gave would satisfy this criterion for the cardiovascular signal. All of the routines used to perform these operations are in appendix B (see peak.m, peakcard.m, and peaklr.m).

In order to determine the I/E ratio, it was necessary to find the valleys of the respiratory signals as well as the peaks. The method used to find the valleys was the same as that used to find the peaks (see appendix B valley.m and valleylr.m). The I/E ratio was found by the following method. First the time that a valley occurred was subtracted from the time that a peak occurred. Then the time that the peak occurred was subtracted from the time that the next valley occurred. The first value was then divided by the second value (see appendix B ie.m and ieie.m).

6.1 Conclusion

A vector of features was created by the program featurev.m which first executed all of the preprocessing routines. The program then extracted features for all of the questions using the times specified in table 4. This program extracted features from all polygraph files in a directory and produced a set of vectors. These vectors were then used for training and testing of a fuzzy K nearest neighbor classifier. For details on the methods used for training and testing as well as the frequency and correlation domain features used in the study refer to Dastmalchi [14]. For details on the K nearest neighbor algorithm refer to Layeghi [15].

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Appendix A

Preprocessing Programs

```
function y = dercd(var)

% This extracts the derivative of a lowpass
% filtered version of the cardio signal.
%
% To use this command the user must enter the file name
%
% eg.   dercd(variable name)

q = detlc(var);  % detrends the lower frequencies
                 % of the cardio signal

e = diff(q);     % differentiates the lower
                 % frequencies of the cardio signal

x = e/std(e);

y = [x',x(length(x))']';
```

```
function y = detgsr(var)

% This function detrends the gsr
%
% To use this command the user must enter the file name
%
% eg.   detgsr(file name)

dtrnd = detrend(var(:,1));
                                     % elliminates dc trends in signal
                                     % eg. a line added to the signal
window = 100;

dtrnd = [dtrnd', zeros(window/2 - 1,1)']';
                             % adds zeros to end of signal so that no
                             % information is lost during filter delay


b = fir1(window,.03);
x = filter(b,1,dtrnd);
q = x/std(x);
l = length(q);

y = q(window/2:l);                       % compensate for time delay
```

```
function y = dethic(var)

% This function detrendeds the high frequencies
% of the cardio signal.
%
% To use this command the user must enter the file name
%
% eg.   dethic(file name)

dtrnd = detrend(var(:,2));  % elliminates dc trends in signal
                            % eg. a line added to the signal

window = 134;

dtrnd = [dtrnd', zeros(window/2 - 1,1)']';
                          % adds zeros to end of signal so that no
                          % information is lost during filter delay


b = fir1(window,.035,'high');
                          % filter to elliminate low frequencies
x = filter(b,1,dtrnd);
q = x/std(x);

l = length(q);

y = q(window/2:l);             % compensate for time delay
```

```
function y = detlc(var)

% This function extracts and detrends the low
% frequencies of the cardio signal
%
% To use this command the user must enter the file name
%
% eg.   detlc(file name)

dtrnd = detrend(var(:,2));  % elliminates dc trends in signal
                            % eg. a line added to the signal
window = 134;

dtrnd = [dtrnd', zeros(window/2 - 1,1)']';
                        % adds zeros to end of signal so that no
                        % information is lost during filter delay

b = fir1(window,.035);    % filter to elliminate high frequencies
x = filter(b,1,dtrnd);
q = x/std(x);

l = length(q);

y = q(window/2:l);        % compensate for time delay
```

```
function y = detlr(var)

% This function extracts and detrends the lower respiratory signal
%
% To use this command the user must enter the file name
%
% eg.   detltr(file name)

dtrnd = detrend(var(:,4)); % elliminates dc trends in signal
                           % eg. a line added to the signal
window = 240;

dtrnd = [dtrnd', zeros(window/2 - 1,1)']';
                        % adds zeros to end of signal so that no
                        % information is lost during filter delay


b = fir1(window,.083);     % filter to elliminate noise
x = filter(b,1,dtrnd);
q = x/std(x);

l = length(q);

y = q(window/2:l);          % compensate for time delay
```

```
function y = detur(var)

% This function detrends the upper respiratory signal
%
% To use this command the user must enter the file
%
% eg.   detur(file name)

dtrnd = detrend(var(:,3));  % elliminates dc trends in signal
                            % eg. a line added to the signal
window = 240;

dtrnd = [dtrnd', zeros(window/2 - 1,1)']';
                          % adds zeros to end of signal so that no
                          % information is lost during filter delay


b = fir1(window,.08);           % filter to elliminate noise
x = filter(b,1,dtrnd);
q = x/std(x);

l = length(q);

y = q(window/2:l);               % compensate for time delay
```

Appendix B

Feature Extraction Programs

```
function [x,y,z] = featurev(file_name,relevant,irrelevant,control,features)

% This function produces a feature vector for a given file
% Relevent, irrelevent, and control are vectors which contain
% the questions these features are extracted from.
%
% eg. featurev(t79,[3 5],[1 4], [6 10],feature_list)

% The above example gives the features for
% the file t79 of the 3rd and 5th question which are relevent in this
% MGQT format, the 1st and 4th question which are irrelevent
% and the 6th and 10th questions which are control

% feature_list=['10mean(frag ) ';
%               '20curve(frag )';
%               '30area(frag ) '];


feature_list = features



% The channels are ordered as follows:
% 1:GSR, 2:HiCardio, 3:LowCardio, 4:DerLowCardio, 5:LowResp, 6:UpResp


% This is a matrix of the time delay after asking a question to start of extracting
% the feature, and finish extracting the feature for each channel.

Times=[ 2, 14;
        3, 9 ;
        2, 18;
        0, 8 ;
        2, 18;
        2, 18];

% These are preprocessing functions.
Preprocess=[    'detgsr';
                'dethic';
                'detlc ';
                'dercd ';
                'detlr ';
                'detur '];

data=zeros(6,length(file_name(:,5)));
% Standardize and detrend the channels and derive new channels

for i=1:6,
        data(i,:)=eval([Preprocess(i,:),'(file_name)'])';
end
```

```
marker = file_name(:,5);    % 0 begin test and end test
                            % 0 examiner begins asking question
                            % 1 examiner finishes asking question
                            % 2 subject begins response to question
                            % 9 does not mark an event

begin = find(marker == 0);    % finds indecies where marker = 0 (question begins)
begin=begin(2:length(begin));    % elliminates the marker at the beginning of the test

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% This for loop creates feature vectors for each relevant quesion
%
% eg x = [mean(gsr),std(gsr),area(gsr),mean(lr),std(lr),area(lr),etc.........
%         curve length,amplitude of peaks,# of peaks]
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

feature_count=1;

for i = 1:length(relevant),
        question=relevant(i);

        for j=1:length(feature_list(:,1))
                channel_number=eval(feature_list(j,1));
                second_channel=eval(feature_list(j,2));
                st=begin(question)+30*Times(channel_number,1);
                fn=begin(question)+30*Times(channel_number,2);
          st2=begin(question)-30*Times(channel_number,2);
          fn2=begin(question)-30*Times(channel_number,1);
                fr=feature_list(j,3:length(feature_list(1,:)));
                frag=data(channel_number,st:fn);
                frag2 = data(channel_number,st2:fn2);
                if second_channel ~= 0
                        st3=begin(question)+30*Times(second_channel,1);
                fn3=begin(question)+30*Times(second_channel,2);
                        frag3 = data(second_channel,st3:fn3);
                end
                tempy=eval(fr);
          for m = 1:length(tempy)
             x(feature_count) = tempy(m);
                  feature_count=feature_count+1;
          end
        end
end
%------------------------------------------------------------------
% Irrelevant questions

feature_count=1;

for i = 1:length(irrelevant),
        question=irrelevant(i);

        for j=1:length(feature_list(:,1))
                channel_number=eval(feature_list(j,1));
```

```
                second_channel=eval(feature_list(j,2));
                st=begin(question)+30*Times(channel_number,1);
                fn=begin(question)+30*Times(channel_number,2);
           st2=begin(question)-30*Times(channel_number,2);
           fn2=begin(question)-30*Times(channel_number,1);
                fr=feature_list(j,3:length(feature_list(1,:)));
                frag=data(channel_number,st:fn);
                frag2 = data(channel_number,st2:fn2);
                if second_channel ~= 0
                        st3=begin(question)+30*Times(second_channel,1);
                fn3=begin(question)+30*Times(second_channel,2);
                        frag3 = data(second_channel,st3:fn3);
                end
                tempy=eval(fr);
           for m = 1:length(tempy)
              y(feature_count) = tempy(m);
                  feature_count=feature_count+1;
           end
        end
end

%-------------------------------------------------------------------
% Control questions

feature_count=1;

for i = 1:length(control),
        question=control(i);

        for j=1:length(feature_list(:,1))
                channel_number=eval(feature_list(j,1));
                second_channel=eval(feature_list(j,2));
                st=begin(question)+30*Times(channel_number,1);
                fn=begin(question)+30*Times(channel_number,2);
           st2=begin(question)-30*Times(channel_number,2);
           fn2=begin(question)-30*Times(channel_number,1);
                fr=feature_list(j,3:length(feature_list(1,:)));
                frag=data(channel_number,st:fn);
                frag2 = data(channel_number,st2:fn2);
                if second_channel ~= 0
                        st3=begin(question)+30*Times(second_channel,1);
                fn3=begin(question)+30*Times(second_channel,2);
                        frag3 = data(second_channel,st3:fn3);
                end
                tempy=eval(fr);
           for m = 1:length(tempy)
              z(feature_count) = tempy(m);
                  feature_count=feature_count+1;
           end
        end
end
```

```
function y = ampcard(var)

% This function finds the average of the amplitudes
% of the peaks in the high
% cardio signal over a specified period of time.
%
% To use this command the user must enter the
% file name and the start and finish points
% of the signal to be displayed
%
% eg.   ampcard(variable name)

p = peakcard(var);       % the indecies of the peaks

for n = 1:length(p)

   q(n) = var(p(n));     % amplitude of the peaks

end

y = sum(q)/length(q);
```

```
function y = ampr(var)

% This function finds the average of the
% amplitudes of the peaks in the lower
% respiratory signal over a specified period of time.
%
% To use this command the user must
% enter the variable name
%
% eg.   ampr(variable name)

p = peaklr(var);        % the indecies of the peaks

for n = 1:length(p)

   q(n) = var(p(n));    % amplitude of the peaks

end

y = sum(q)/length(q);
```

```
function y = curve(var)

% This function finds the length of the variable
%
% To use this command the user must enter the
% variable name and the start and finish points
% of the signal to be displayed
%
% eg.   curve(variable name)


x = sqrt(diff(var).^2 + 1);
y = sum(x);
```

```
function y = ie(var)

% This function takes the i/e ratio of the respiratory signals.
%
% To use this command the user must enter the variable name
%
% eg.   ie(variable name)

p = peaklr(var);          % finds the indices of
                          % the peaks in a signal and puts them
                          % in a vector a
plength = length(p);

v = valleylr(var);         % finds the indices of the
                           % valleys in a signal and puts them
                           % in a vector b
vlength = length(v);

if vlength < 2 | plength < 2        % check that enough peaks
                                    % and valleys exist for
                                    % the calculation to be done

   message = ' Warning !!!! Not enough data'

end

if p(1) > v(1)

   for n = 1:vlength - 1

       q = p(n) - v(n);          % calculates a vector of
                                 % e/i ratios for the given
                                 % time period

       z = v(n + 1) - p(n);

       e(n) = q ./ z;
   end

end

if p(1) < v(1)

   for n = 1:vlength - 1

       q = p(n + 1) - v(n);      % calculates a vector of
                                 % e/i ratios for the peaks
                                 % and valleys in the
                                 % given time period

       z = v(n + 1) - p(n + 1);
```

```
        e(n) = q ./ z;
    end

end

y = mean(e);
```

```
function y = ieie(var1,var2)

% This function takes the i/e ratio of the respiratory signals
% before and after a question is asked.  It then divides the two
% values.
%
% To use this command the user must enter the variable name
%
% eg.   ieie(variable name1, variable name2)

a = ie(var1);

b = ie(var2);

y = a/b;
```

```
function y = peak(var)

% This function finds the peaks in a signal and returns the index
% It also creates a plot of the variable with the peaks marked
%
% To use this command the user must enter the variable name
% of the signal to be displayed
%
% eg.   peak(variable name)

q = diff(var);       % differentiates the variable

z = q>0;             % z = 1 if q is greater than 0

f = diff(z);         % 2nd derivative of the variable

a = f<0;

y = find(a);         % finds the indices where the 2nd derivative
                     % is -1 which indicates peak
```

```
function y = peakcard(var)

% This function finds the peaks in
% the cardio signal and returns a vector of
% indexes where they occur.
%
% To use this command the user must enter the variable name
%
% eg.   peakcard(variable name)


ty = peak(var);

if ty(1) < 8
        ty = ty(2:length(ty));
end

if ty(length(ty)) > length(var) - 8
        ty = ty(1:length(ty)-1);
end

for n = 1:length(ty);
                        % finds the maximum peak over a 10 point s
pan


     temp = var(ty(n)-8 : ty(n)+8);

     z(n) = ty(n) - 9 + find(temp == max(temp));
                                 % finds the time that the peak
                                 % occurs in the original signal
end

for n = 1:length(z)-1  % elliminates duplicate indicies

    if z(n) == z(n+1)

         z(n) = 0;

     end

end

ind = find(z);               % finds indecies of elements
                             % that are not equal to zero

for n = 1:length(ind)        % elliminates 0 elements

     z(n) = z(ind(n));

end
```

```
y = z(1:length(ind));

% pmark = zeros(1,length(var)); % a vector of 1's where peaks occu
r
                                % 0's everywhere else
% pmark(y) = ones(1,length(y));

% plot(var,'r')

% title('lr marked with peaks')

% hold on

% plot(5*pmark,'g')

% hold off
```

```
function y = peaklr(var)

% This function finds the peaks
% in the lr signal and returns a vector
% of indecies where they occur.
%
% To use this command the user must enter the variable name
%
% eg.   peaklr(variable name)


[b,a] = butter(4,.034);                 % elliminate noise
filtout = filtfilt(b,a,var);

ty = peak(filtout);  % finds the time that the
                     % peaks of filtered lr signal occur

if ty(1) < 20
        ty = ty(2:length(ty));
end

if ty(length(ty)) > length(var) - 20
        ty = ty(1:length(ty)-1);
end

for n = 1:length(ty)

     temp = var(ty(n)-20:ty(n)+20);
     z(n) = ty(n) - 21 + find(temp == max(temp));
                       % finds the time that the peak occurs in
                       % the original signal
end

for n = 1:length(z)-1           % elliminates duplicate indicies

    if z(n) == z(n+1)

          z(n) = 0;

     end

end

ind = find(z);          % finds indecies of elements
                        % that are not equal to zero

for n = 1:length(ind)  % elliminates 0 elements

     z(n) = z(ind(n));

end
```

```
y = z(1:length(ind));
```

```
function y = peaknumc(var)

% This function finds the number of
% peaks in the high cardio signal
%
% To use this command the user
% must enter the variable name
%
% eg.   peaknumc(variable name)

p = peakcard(var);        % the indecies of the peaks

y = length(p);
```

```
function y = peaknumr(var)

% This function finds the number
% of peaks in the respiratory signal
%
% To use this command the user
% must enter the variable name
%
% eg.   peaknumr(variable name)

p = peaklr(var);        % the indecies of the peaks

y = length(p);
```

```
feature_list=[  '10mean(frag)           ';
                '10curve(frag)          ';
                '10area(frag)           ';
                '20mean(frag)           ';
                '20curve(frag)          ';
                '20area(frag)           ';
                '20ampcard(frag)        ';
                '20peaknumc(frag)       ';
                '30mean(frag)           ';
                '30curve(frag)          ';
                '30area(frag)           ';
                '40mean(frag)           ';
                '40curve(frag)          ';
                '40area(frag)           ';
                '50mean(frag)           ';
                '50curve(frag)          ';
                '50area(frag)           ';
                '50ampr(frag)           ';
                '50peaknumr(frag)       ';
                '50ie(frag)             ';
                '50ieie(frag, frag2)    ';
                '60mean(frag)           ';
                '60curve(frag)          ';
                '60area(frag)           ';
                '60ampr(frag)           ';
                '60peaknumr(frag)       ';
                '60ie(frag)             ';
                '60ieie(frag, frag2)    '];
[x y z] = featurev(t79,[1 2],[3 4],[6 10],feature_list)
```

```
function y = valcard(var,start,finish)

% This function finds the valleys in
% the lr signal and returns a vector of indexes where
% they occur
%
% To use this command the user must enter the
%  file name and the start and finish points
% of the signal to be displayed
%
% eg.   valcard(file name, start, finish)


k = hicardio(var,start,finish);


[b,a] = butter(4,.034);        % elliminate high frequencies
filtout = k; % filtfilt(b,a,k);

ty = valley(filtout,start,finish) % finds the time that the
                                  % peaks of filtered lr signal oc
cur

l = length(ty);


for n = 1:l

     temp = k(max(1,ty(n)-10+start) : min(ty(n)+10+start,length(k)
));

     if ty(n)<10
        dd=length(temp)/2+1;
     else
        dd=11;
     end

     y(n) = ty(n) - dd + find(temp == min(temp));
                           % finds the time that the peak occurs in
                           % the original signal
end

vmark = zeros(1,finish - start); % a vector of 1's where peaks occ
ur
                                 % 0's everywhere else
vmark(y) = ones(1,length(y));

subplot(211),plot(k(start:finish),'r')
```

```
title('lr marked with peaks')
hold on
plot(-5*vmark,'g')
hold off
subplot(212),plot(filtout(start:finish),'r')
title('filtered lr marked with peaks')
hold on
plot(vmark,'g')
hold off
% subplot(223),plot(k(start:finish),'r')
% hold on
% plot(5*a(1:finish - start - 3),'g')
% hold off
% subplot(224),plot(x)
% subplot(111)
```

```
function y = valley(var)

% This function finds the
% valleys in a signal and returns the index

% To use this command the user
% must enter the variable name
%
% eg.   valley(variable name)

q = diff(var);          % differentiates the variable

z = q > 0;      % z = 1 if q is greater than 0

f = diff(z);    % 2nd derivative of variable

a = f > 0;      % finds valleys

y = find(a);    % finds the indices where the 2nd derivative
                % is +1 which indicates valleys
```

```
function y = valleylr(var)

% This function finds the valleys in
% the lr signal and returns a vector of
% indecies where they occur
%
% To use this command the user must enter the variable name
%
% eg.   valleylr(variable name)


[b,a] = butter(4,.034);        % elliminate high frequencies
filtout = filtfilt(b,a,var);

ty = valley(filtout);     % finds the time that the
                          % peaks of filtered lr signal occur

for n = 1:length(ty)

     temp = var(max(1,ty(n)-20) : min(ty(n)+20,length(var)));

     if ty(n)<20
        dd=length(temp)/2+1;
     else
        dd=21;
     end

     z(n) = ty(n) - dd + find(temp == min(temp));
                         % finds the time that the peak occurs in
                         % the original signal
end

for n = 1:length(z)-1     % elliminates duplicate indicies

    if z(n) == z(n+1)

          z(n) = 0;

     end

end

ind = find(z);            % finds indecies of elements
                          % that are not equal to zero

for n = 1:length(ind)     % elliminates 0 elements

     z(n) = z(ind(n));

end
```

```
y = z(1:length(ind));
```

Appendix B: Feature Analysis of the Polygraph

Mitra Dastmalchi

Fall 1993

Features Analysis of the Polygraph

A Report
Presented to
The Faculty of the Department of Electrical Engineering
San Jose State University

In Partial Fulfillment
of the Requirements for the degree
of Master of Science

By
Mitra Dastmalchi
December 1993

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I express may sincere appreciation to all of those who have contributed to this project. Special recognition goes to my advisor, Dr. Ben Knapp, for his advise and encouragement. I am also grateful for the help of my partners, Shahab Layeghi and Eric Jacobs. Especially shahab, for his support and valuable suggestions.

Feature Analysis of the polygraph

By

Mitra Dastmalchi

Sponsor: Dr. Benjamin Knapp

Approved: ____________________ __________

Sponsors Signature Date

Graduate Commitee

	Name	Date
Dr. Sun Chiao	____________________	__________
Dr. Richard Duda	____________________	__________
Dr. Peter Reischl	____________________	__________
Dr. Avtar Singh	____________________	__________

Graduate Coordinator

Dr. Rangaiya Rao	____________________	__________

Mitra Dastmalchi, 25800 Industrial Blvd Hayward, CA 94545 Tel: (510)782-3104

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I express may sincere appreciation to all of those who have contributed to this project. Special recognition goes to my advisor, Dr. Ben Knapp, for his advise and encouragement. I am also grateful for the help of my partner, Shahab Layeghi and Eric Jacobs. Especially shahab, for his support and valuable suggestions.

Contents

0 Introduction

The polygraph examination is one of the most popular methods to measure deception. Polygraph tests are used in criminal investigations to determine if a suspect is being deceptive when answering the questions concerning a crime. During a polygraph test, the subject is asked a series of control, relevant and irrelevant questions that provide physiological responses for comparison with question that are relevant to the investigation. The three physiological responses that are currently measured are electrocardiogram, galvanic skin response and respiration. The controversy surrounding the use of polygraph tests centers on the subjective judgment of polygraph examiners in classifying the subject as deceptive or non-deceptive. The object of this project is to develop an automatic scoring system to overcome this perception. The computer algorithm will be able to use more sophisticated techniques than human examiners, should be more accurate and will ensure consistency from case to case.

In order to implement the automatic scoring system, two main algorithms were developed. These were: the feature extraction algorithm, which process the polygraph data in three time, correlation and frequency domains, and the fuzzy classifier algorithm, which accepts the features and determines the possibility of deception. Because of the nature of the input, fuzzy logic was chosen to implement the system which gives the possibility of belonging of an input to each class. Initially, a set of features based on physiological reactions were selected. Then, the fuzzy K-nearest neighbor classifier was used to classify the features.

1 Polygraph

1.1 Polygraph Examination

The primary use of the polygraph test is during the investigation stage of the criminal justice process. In addition to the significance role in criminal justice, they are also used for national security, intelligence and counterintelligence activities [1]. The three physiological responses currently obtained from a polygraph examination are electrocardiogram, respiration and galvanic skin response. Electrocardiogram is measured by placing a standard cuff on the arm over the brachial artery. Respiration is monitored by placing rubber tubes around the abdominal area of the subject. Skin conductivity is measured by electrodes placed on two fingers of the same hand of the subject [1].

The effectiveness of a polygraph examination is often the result of the test format that is used. A polygraph test format is an ordered combination of relevant question about an issue, control questions that provide physiological responses for comparison and irrelevant questions that act as a buffer [1]. An example or a relevant question is, " did you embezzle any of the missing $12000?" The corresponding control question would be about stealing; an example is, "did you ever steal money or property from an employer?" The example of an irrelevant question is, " is your name John?" Irrelevant questions are answered truthfully and are not stressful. The rational for scoring these tests is that a deceptive subject will be more threatened by the relevant question than by the control question while a non deceptive subject will be more threatened by the control questions than the relevant question.

Polygraph charts are usually analyzed by a human interpreter for evidence of truth or deception. A control question polygraph chart usually consists of 3 sets of control relevant question pairs separated by neutral questions. The examiner scores the charts by comparing each relevant question. For each of three physiological responses, he will give a numerical score ranging from -3 t0 +3, depending on the magnitude of the difference. He then adds up scores for all control relevant pairs. If the score is below threshold value, he scores the chart as deceptive or non deceptive.

Sometimes the examiner can not make a clear decision and must score the chart as inconclusive. The examiner's decision will be based on his or her experience and training. For example, a change in the polygraph tracing considered by one examiner as a physiological changes, may be considered by another as an artifact of the recording system. In an effort to eliminate the inconsistencies involved in interpreting polygraph data, computer algorithm are being developed.

1.2 History[1]

The first attempt to use a scientific instrument in an effort to detect deception occurred around 1895 [2]. That was the year that Cesar Lombroso published the results of his experiments in which a hydrosphygmograph was used to measure the blood pressure-pulse changes of criminals in order to determine whether or not they were deceptive. Although the hydrosphygmograph was originally intended to be used for medical purposes, Lombroso found that it worked well for lie detection. Lombroso may have been the first to use a peak of tension test format. This was done by showing a suspect a series of photographs of children, one being the victim of sexual assault. If the suspect did not react more to the victims picture than the pictures of the other children, Lombroso concluded that the suspect did not know what the victim looked like and therefore was not the alleged perpetrator.

In 1914 Vittorio Benussi published his research on predicting deception by measuring recorded respiration tracings [3]. He found that if the length of inspiration were divide by the length of expiration, the ratio would be larger after lying than before lying and also before telling the truth than after telling the truth. In 1921 John A. Larson constructed an instrument capable of simultaneously recording blood pressure pulse and respiration during an examination [2][3]. Larson reported accurate results which prompted Leonarde Keeler to construct a better version of this instrument in 1926 [2][3].

The use of galvanic skin response in lie detection began during the turn of the century. It's usefulness, however, did not become evident until the 1930's during which time several articles written by Father Walter G. Summers of Fordham University in New York [3]. In these articles he reports over 90 criminal cases in which examination using the galvanic skin response had all been successful and confirmed by confession or supplementary evidence. The usefulness of the galvanic skin response prompted Keeler to add an galvanometer to his polygraph. At the time of Keelers death in 1949, the Keeler Polygraph recorded blood pressure-pulse, respiration, and galvanic skin response [3].

1.3 Modern Test Formats[1]

The effectiveness of a polygraph examination is often the result of the test format that is used. A polygraph test format consists of an ordered combination of relevant questions about an issue, control questions that provide a physical response for comparison, and irrelevant questions that also provide a response or the lack of a response for comparison [1][3]. Three general types of test formats are in use today. These are Control Question Tests, Relevant-Irrelevant Tests, and Concealed Knowledge Tests. Each of the general test formats may have a number of more specific variations. Each test consists of two to

[1]These sections were exerpted from Jacobs [10].

five charts containing a prescribed series of questions. The test format that is used in an examination is determined by the test objective [2][3].

The concealed knowledge test, also called peak of tension test, is used when facts about a crime are known only by the investigators and not by the public. In this case, a subject would not know the facts unless he or she was guilty of the crime. For example, if a gun was used in a crime and the public did not know the caliber, an examiner could ask a suspect if it was a 22 caliber, a 38 caliber, or a 9 mm. If the gun used was a 9 mm and the suspect was deceptive, a polygraph chart would probably indicate evidence of deception.

A control question test is often used in criminal investigations. Relevant-Irrelevant tests are usually used to test people trying to obtain security clearance or get a job. In this test, relevant questions are compared to irrelevant questions. Very few control questions are asked. The purpose of control questions in this test is to make sure that the subject is capable of reacting at all.

1.4 Present Day Equipment[2]

The most popular polygraph machines today are the Reid Polygraph developed in 1945 and the Axciton Systems computerized polygraph developed in 1989 [1][4]. The Reid polygraph scrolls a piece of paper under pens that record the biological signals. The Axciton polygraph digitizes physiological signals and uses a computer to process them. The sampling frequency of the Axciton machine is 30 Hz. Axciton provides a computer based system for ranking the subject responses but allows printouts of the charts to be scored by hand the traditional way.

Both machines record the same biological signals using standard methods. Blood pressure is measured by placing a standard blood pressure cuff on the arm over the brachial artery. Respiration is monitored by placing rubber tubes around the abdominal area and the chest of the subject. This results in two signals, an upper and lower respiratory signal. Skin conductivity is measured by placing electrodes on two fingers of the same hand.

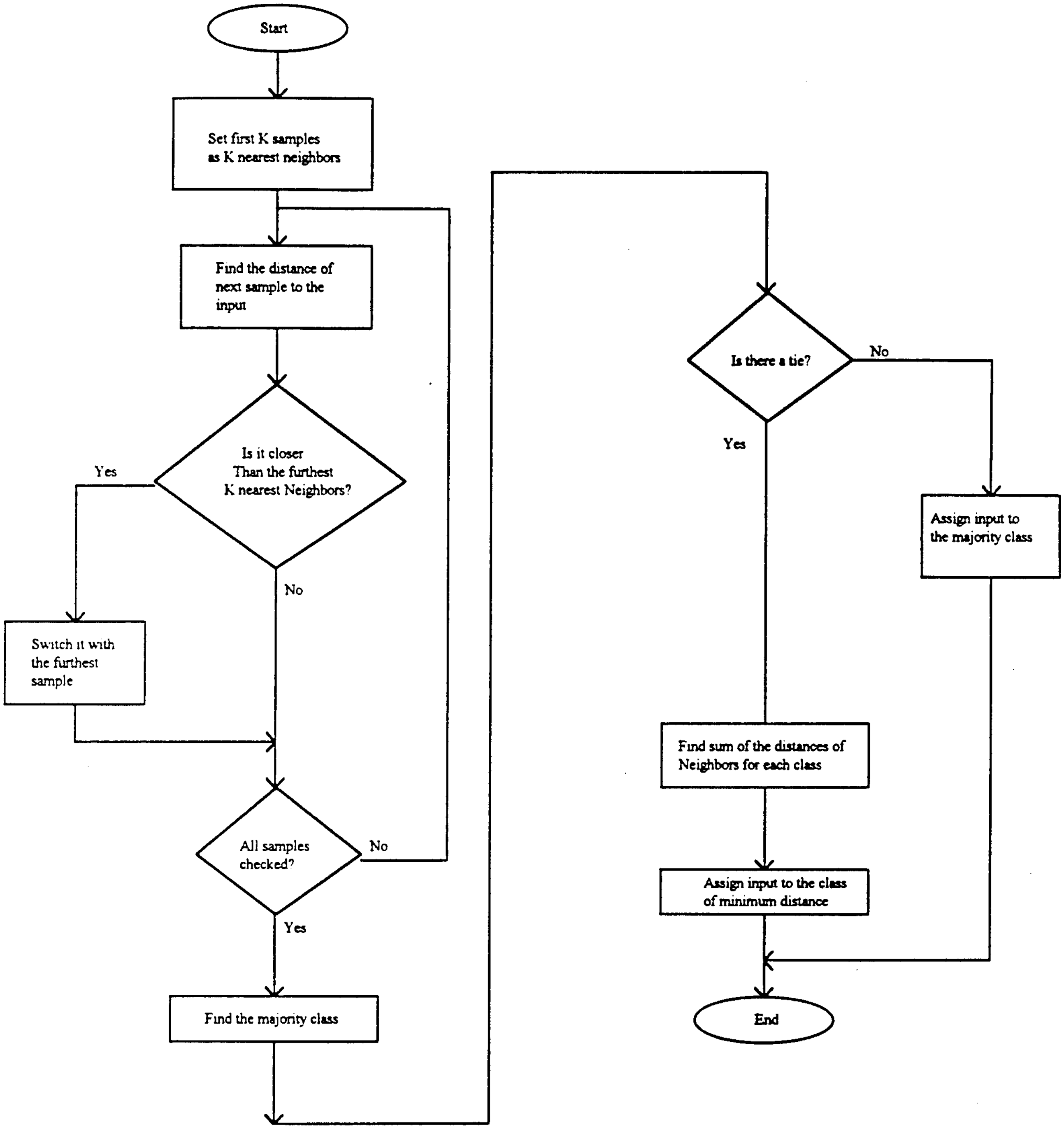
[2]This section was exerpted from Jacobs [10].

2 Classifier Algorithm

2.1 K-Nearest Neighbor Algorithm[3]

K-nearest neighbor algorithm is a supervised classification method. There is no need for the training or adjusting the classifier. A set of labeled input samples is given to the classifier. When a new sample is given to the system, it finds its K nearest neighboring samples, and assigns this sample to the class that the majority of the neighbors belong to. K could be any positive integer. When K is set to 1, the algorithm is called the nearest neighbor algorithm. In this case each new sample is assigned to the class of its nearest neighbor. If K is greater than 1, it is possible that there is no majority class. To remove this tie, the sum of the distances of the new sample to its neighbors in each class is computed and the sample is assigned to the class that has the minimum distance. The main advantage of using this method is that the samples of each class are not needed to cluster in a pre specified shape. For example, for a two class classification, the K-nearest neighbor classifier can still give very good results if the samples of each class are clustered in two distinct points in the space. The algorithm for the K nearest neighbor is shown in flow chart 1. It is supposed that C is the number of classes, K is the number of neighbors in KNN, x_i x_i is the *ith* labeled sample and y is the input to be classified.

[3]This section was exerpted from Layeghi [11].



Flow chart 1. Fuzzy K Nearest Neighbor Algorithm

The fuzzy K nearest neighbor algorithm uses the same idea of conventional K nearest neighbor algorithm, that is finding the K samples that are closest to sample to be classified. But there is a conceptual difference in classification. When fuzzy classification is used, the input is not assigned to a single class. Instead, the degree of belongings of the input to each class is determined by the classifier. By using this method more information is obtained about the input. For example if the result of classification determines membership of an input to class A is 0.9 and to class B is 0.1, it means the input belongs to class A with a very good possibility. But if the membership to class A is 0.55 and to class B is 0.45, it means that we cannot be very sure about the classification of the input. If the crisp classifier is used, in both cases the input will be assigned to class A and no further information is obtained.

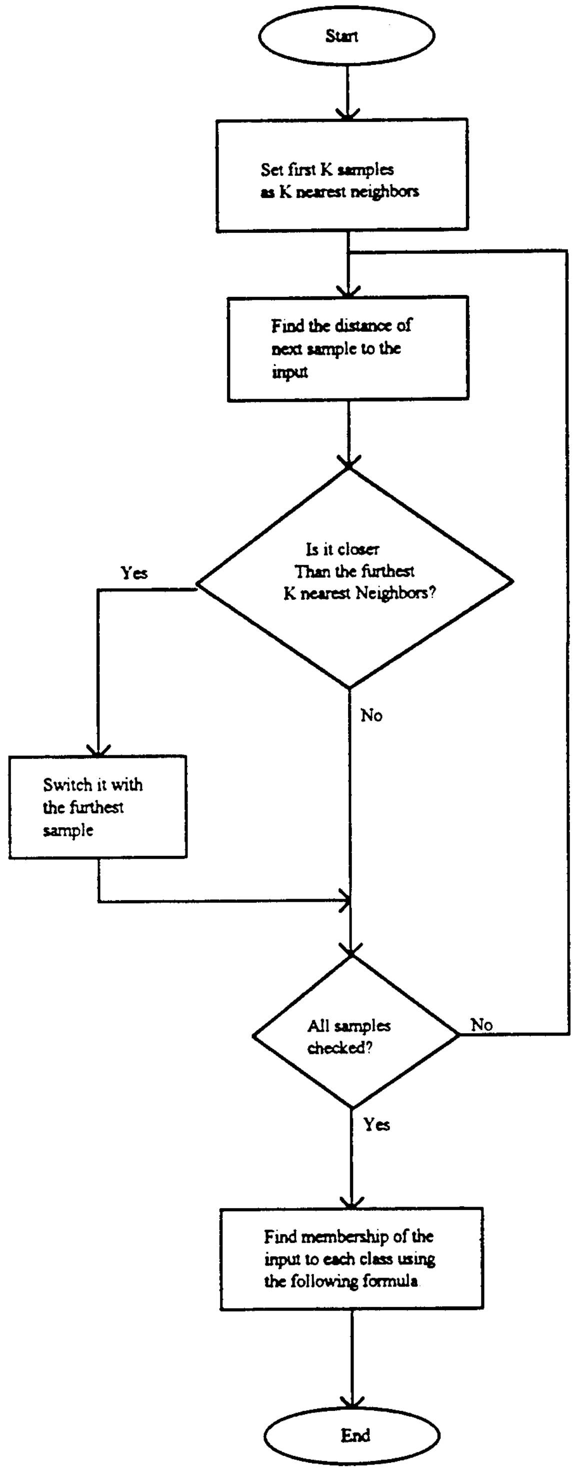
Refer to [5] [6] for more detailed discussions about fuzzy K nearest neighbor algorithms. The flowchart for a fuzzy K nearest neighbor classifier is drawn in flow chart 2.

The first step in the fuzzy K nearest neighbor algorithm is the same as first step in crisp classifier. In both cases K nearest neighbors of the input are found. While in crisp classifier the majority class of the neighbors is assigned to the input, in Fuzzy classifier membership of the input to each class should be found. In order to do so the membership vector of each sample is combined to obtain the membership vector of the input. If the samples are crisply classified, membership vectors should be assigned to them. One method to do so is to assign the membership of 1 to the class that it belongs to, and membership of 0 to other classes. Other methods assign different memberships to the samples according to its distance from the mean of the class, or the distances from the nearby samples of its own class and the other classes.

When the membership vectors of the labeled samples are specified, they are combined to find the membership vector of the unknown class. This procedure should be done in a way that samples that are closer to the input have more effect on the resultant membership function. The following formula uses the inverse distance to weigh the membership functions. x is the input to be classified, x_j is the jth nearest neighbor and u_{ij} is the membership of the jth nearest neighbor of the input in class i. D(x,y) is a distance measure between the vectors x and y which could be the Euclidean distance.

$$u_i(x) = \frac{\sum_{j=1}^{K} u_{ij}(1/D(x,x_j)^{\frac{1}{m-1}})}{\sum_{j=1}^{K}(1/D(x,x_j)^{\frac{1}{m-1}})}$$

m is a parameter that changes the weighing effect of the distance. When m >> 1, all the samples will have the same weight. When m approaches 1, nearest samples have much more effect on the membership value of the input.



Flow chart 2. Fuzzy k nearest neighbor

$$u_i(x) = \frac{\sum_{j=1}^{K} u_{ij} (1 / D(x, x_j)^{\frac{1}{m-1}})}{\sum_{j=1}^{K} (1 / D(x, x_j)^{\frac{1}{m-1}})}$$

3 Frequency and correlation Domain Features

3.1 Preview

The purpose of this chapter is to show how the frequency and correlation domain representations of polygraph signals can be used effectively in polygraph analysis. The first step in analysis of a time series is to plot the data and to obtain simple descriptive measures of the main properties of the series. For some series, in addition to features such as trend, seasonal effect and cyclic changes, more sophisticated features such as mean, variance, auto correlation and frequency content will be required to provide an adequate analysis.

Most physical processes, including polygraph signals, involve a random element in their structures. Currently, human examiners score polygraph tests by analyzing obvious features in the time domain. It is presumed that processing polygraph signals in frequency and correlation domain will provide features which are discriminator between deceptive and non-deceptive subjects. Before finding the frequency domain features the trend in the electrocardiogram channel was eliminated. In order to do so, a high frequency electrocardiogram channel, called heart pulse, is produced by highpass filtering it.

The goal of this chapter is to explain the techniques used to extract appropriate features in frequency and correlation domains. The methods for estimating features of the polygraph signals such as fundamental frequency, spectral density and cross correlation between the channels will be discussed.

3.2 Fundamental Frequency

One feature which is considered important in the frequency domain is the fundamental frequency of the signal. The purpose of finding the fundamental frequency is to classify the way the frequency changes in a specific time segment. The assumption in polygraph signals is that the frequency of the signal changes after a relevant or a control question is asked. Different methods have been proposed to find the fundamental frequency of a signal. One of these methods is using the auto correlation function.

The auto correlation representation of a signal is a convenient way of displaying certain properties of the signal. For example, the auto correlation function of a periodic signal is also periodic with the same period. For periodic signals with period P, the auto correlation function attains a maximum at samples $0, \pm P, \pm 2P, \ldots$. Regardless of the time origin of the signal, the period can be estimated by finding the location of the first maximum in the auto correlation function [7].

This property makes the auto correlation function an attractive basis for estimating periodicity in most signals including the electrocardiogram and respiration signals of the polygraph records. Therefore, a short segment of the signals (electrocardiogram and respiratory) after each question is selected and pre-processed. The auto correlation is then calculated for the windowed segments of the heart pulse and respiratory signals using MATLAB. Figure 1 shows the examples of auto correlation functions computed for heart pulse with N = 150 and upper respiratory with N = 400 sampled at 30 Hz. N is the number of samples .

It is noticeable that the auto correlation functions of the above signals are a mixture of damped exponential and sinusoids. For the heart pulse, peaks occur approximately at multiples of 20 samples indicating a period of 20/30=0.67 seconds or a fundamental frequency of approximately 1.5 Hz. For the upper respiratory, peaks occur approximately at multiples of 133 samples indicating a period of 133/30 = 4.4 seconds or a fundamental frequency of approximately 0.23 Hz.

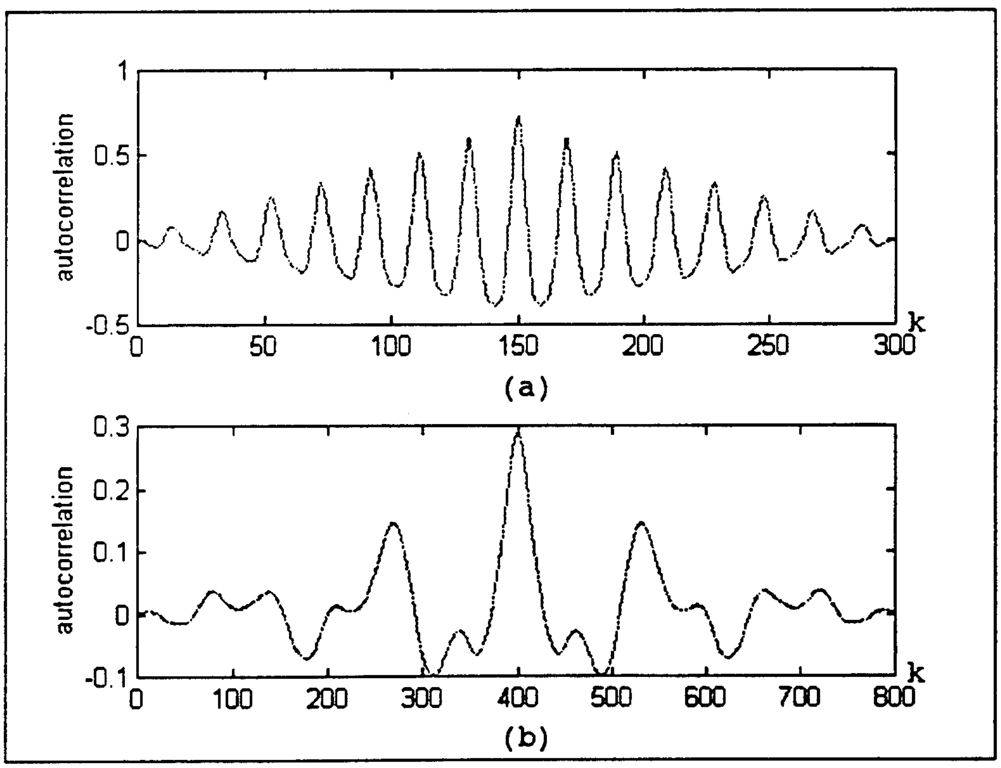


Figure 1. Plots of auto correlation function for (a) heart pulse and (b) upper respiratory where k is the number of samples.

For some subjects, the period of the electrocardiogram or upper respiratory signal changes across the N sample interval. Also, the shape of the signal varies somewhat from period to period. Because of the finite length of segments involved in the computation of auto-correlation, there is less and less data involved in the computation as the lag increases. This leads to the reduction in amplitude of the correlation peaks as lag increases.

An important issue is how N should be chosen to give a good indication of periodicity. Because we are interested in observing changes in signal after the question is asked, N should be small. On the other hand, it should be noted that to get any indication of periodicity in the auto correlation function, the window must have the duration of at least two periods of the waveform. In order to choose the best N, the fundamental frequency for different time frames without overlap were calculated and the results were examined. The fundamental frequencies of heart pulse for the four second frame are shown in Table 1 and 2 in Appendix A. No single value of N is entirely satisfactory because the frequency changes from individual to individual. However, a suitable practical choice for N was chosen on the order of 180 and 480 for heart pulse and upper respiratory respectively.

3.3 Modeling

Detailed information about a time series can be obtained from creating a model. In this section a model will be found for the heart pulse signal. Finding a suitable model for a given time series depends on the properties of the series and the number of observations available. In signal modeling the output signal is known and the model development is based upon the fact that signal points are correlated. Estimated auto correlation function (ACF) of the time series is helpful in identifying which type of ARMA model is appropriate and gives the best representation of the signal.

The ACF of a MA process cuts off at lag q whereas the ACF of an AR process is a mixture of damped exponential and sinusoids and dies out slowly. For example, if r1 is significantly different from zero but the subsequent values of r_k are all close to zero then an MA(1) model is indicated since its theoretical ACF is of this form. Alternatively, if r_1, r_2, r_3 ,.. appear to be decreasing exponentially, then an AR(1) model may be appropriate.

It is usually difficult to find the order of an AR process from the sample ACF alone. A model with too low an order will not represent the properties of the signal. Also a model with too high an order will represent any measurement noise or inaccuracies. Therefore, neither a high order nor a low order model will be a reliable representation of the signal. As a result, method that will determine the model order should be used. One approach is to fit AR processes of progressively higher order, to calculate the squared error for each value of model order (M), and to plot this against model order. It may then be possible to see the value of M where the curve flattens out and the addition of extra parameters gives little improvement in fit. Another approach based upon the principals of prediction is that to increase the model order until the residual process becomes a white noise.

Other criteria have been developed that are based upon concepts in mathematical statistics [9]. The first one is the final prediction error (FPE),

$$\mathrm{FPE} = P\frac{N+M+1}{N-M-1} \tag{3.3a}$$

Where P, N and M are error, number of samples and model order respectively.

The fractional portion of FPE increases with M and accounts for the inaccuracies in estimating the parameters. The other criterion is called Akaike's information criterion (AIC). It is:

$$\mathrm{AIC} = N \ln p^2 + 2P \tag{3.3b}$$

The first criterion tends to have a minimum at values of M that are less than the model order and the second one tends to overestimate model order.

The above criteria were calculated for electrocardiogram signal and the results were plotted in Figure 2. As shown in Figure 2(a), the error decreases but there is no definitive slope change. The largest decrease occurs from order 1 to 2 and the error does not seem to decrease significantly with orders greater than 11. For FPE (Figure 2(b)) and AIC (Figure 2(c)) plots, the error does not decrease much with orders greater than 11. Thus, the order can be approximately 10. The Levinson-Durbin algorithm was used to calculate the AR parameters with order 10 for heart pulse. These parameters were used as features.

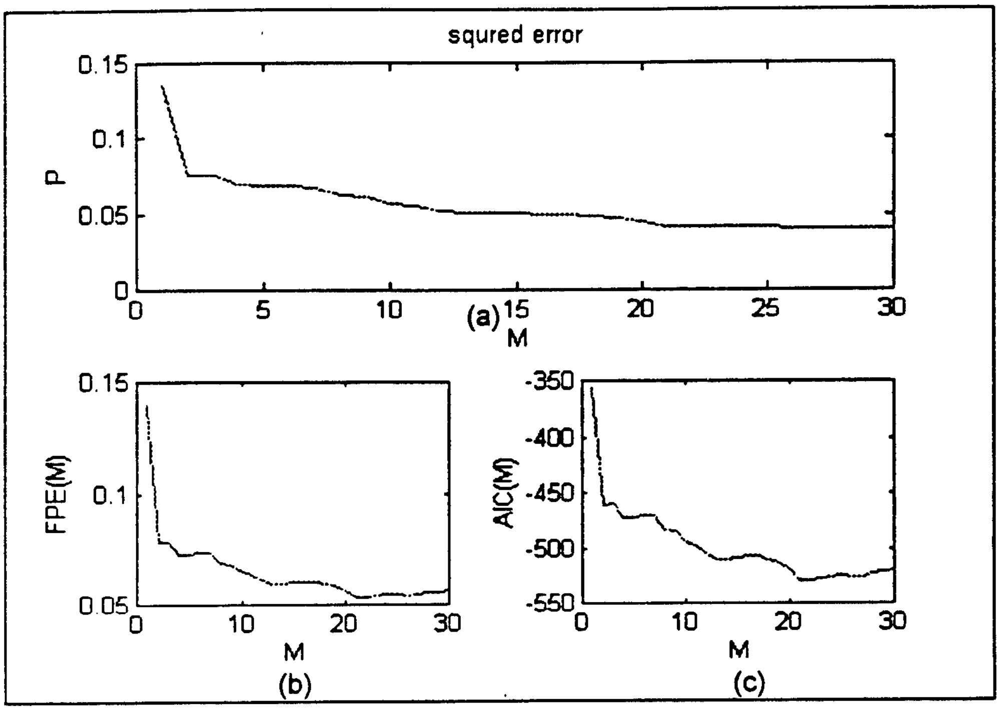


Figure 2. The different criteria for heart pulse versus model order (M): (a) error; (b) FPE; (c) AIC.

3.4 Cross-covariance and cross-correlation functions

In general, it may be necessary to study the interactions between two processes with possibly different scales of measurement or different variances. In polygraph where time series data are generated from more than one channel at a time, features like cross-correlation which contain information about relationships between the channels are extracted. The cross covariance(C_{xy}) and cross correlation function (r_{xy}) are defined as following:

$$C_{xy}(k) = \frac{\sum_{k=1}^{N-1}(X(n) - m_x)(Y(n+k) - m_y)}{N} \qquad [k = 0,1,....(N-1)] \quad (3.4a)$$

$$r_{xy} = Cxy \,/\, \sqrt{[Cxx(0)Cyy(0)]} \quad (3.4b)$$

$$\text{where} \quad m_x = \sum_{k=1}^{N}\frac{X(n)}{N} \qquad m_y = \sum_{k=1}^{N}\frac{Y(n)}{N} \quad (3.4c)$$

$Cxx(0)$ and $Cyy(0)$ are the variances of observations on X and Y respectively.

This estimate is asymptotically unbiased. However, the variance of the estimate depends on the auto correlation functions of the two components. Therefore, for moderately large values of N it is possible for two series, which are actually uncorrelated, to give rise to large cross-correlation coefficients which are actually spurious. Thus, both series should first be filtered to convert them to white noise before computing the cross-correlation function [8].

In order to determine the relationship between the upper respiratory and heart rate, the cross correlation between them was calculated. Figure 3 shows the cross correlation between heart pulse and upper respiratory for a control and a relevant question for two different deceptive and non deceptive cases.

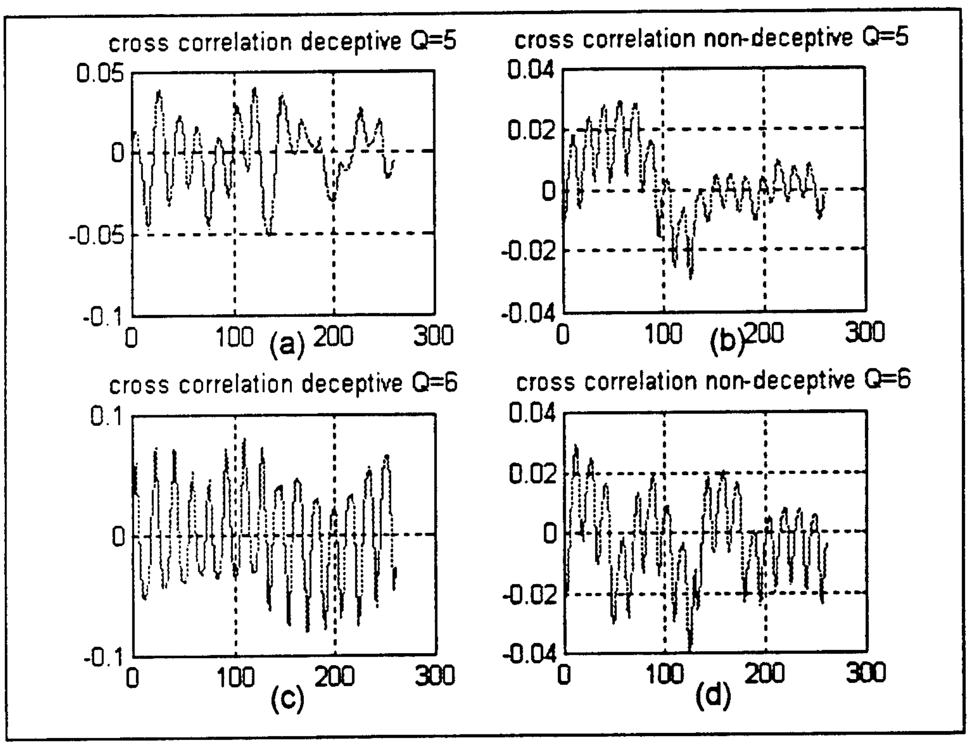


Figure 3. Cross correlation between upper respiratory and heart pulse before modeling. (a) and (b) 90 seconds after relevant question 5. (b) and (c) 90 seconds after control question 6.

3.5 Whitening filter

For a given process {x(n)}, the innovation process {v(n)} is defined as a white noise process such that {v(n)} can be determined from the signal {x(n)} by the whitening filter. The innovations representation of a random process is a powerful analytic tool. The innovation process makes the interpretation of the original process simpler than the original signal. Yet both processes contain the same statistical information. In other words, there is no loss of information as a result of the transformation.

As stated in section 3.4, it is possible for two series, which are actually uncorrelated, to give rise to large cross-correlation coefficients which are actually spurious. Thus, the series should first be filtered to convert them to white noise before computing the cross-correlation function. The AR parameters were used to design the whitening filter. Then, the heart pulse signal was filtered to convert it to white noise.

When the time series is white noise and purely random, the neighboring points of the ACF are uncorrelated. In order to compare the whitening filter output and the theoretical white noise, both the output of the whitening filter and its auto correlation for electrocardiogram were plotted in Figure 4. It is seen that the auto correlation shows high correlation for lag zero (k=175) and small correlation for other lags as it expected.

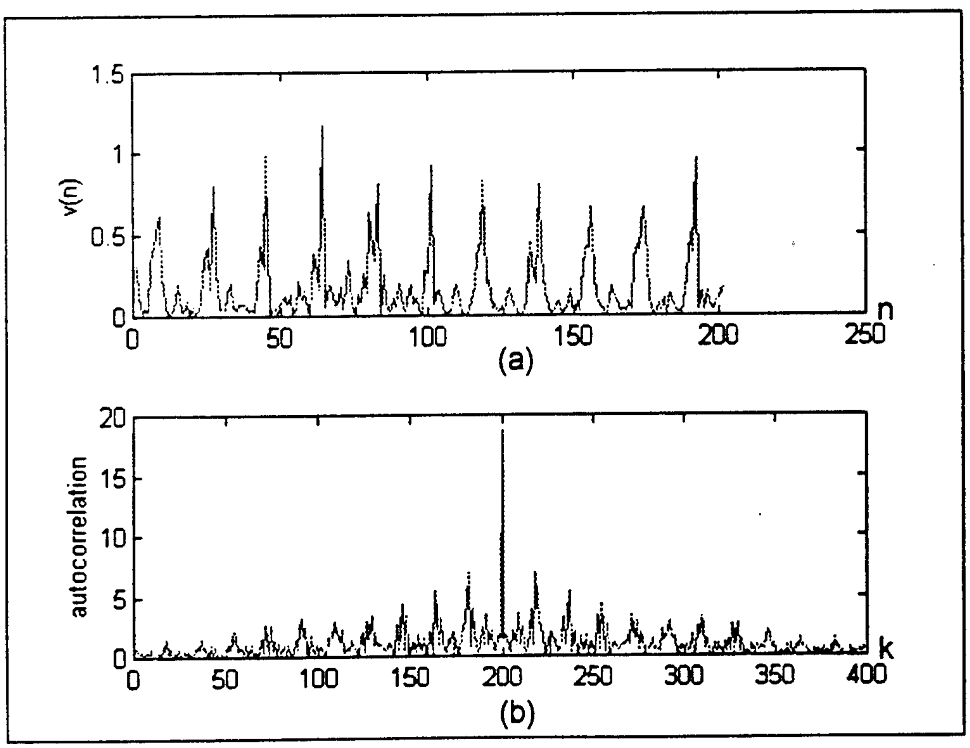


Figure 4. Plots of (a) white noise (output of the whitening filter); (b) auto correlation of the white noise.

The heart pulse and its innovation process (pre whitening filter output) contain the same information. The results of cross-correlation between upper respiratory and heart rate signals after pre whitening are shown in figure 5. It can be seen that the cross-correlation after modeling is similar to the cross correlation before modeling (Figure 2) with less spurious peaks. The maximum and minimum value of cross correlation and their lags were considered as potential features in correlation domain. As presented in figure 5 (b), heart pulse and upper respiratory channels are positively correlated after the 30 to 90 lags (1-3 seconds) and are negatively correlated after 130 lags (4.3 seconds).

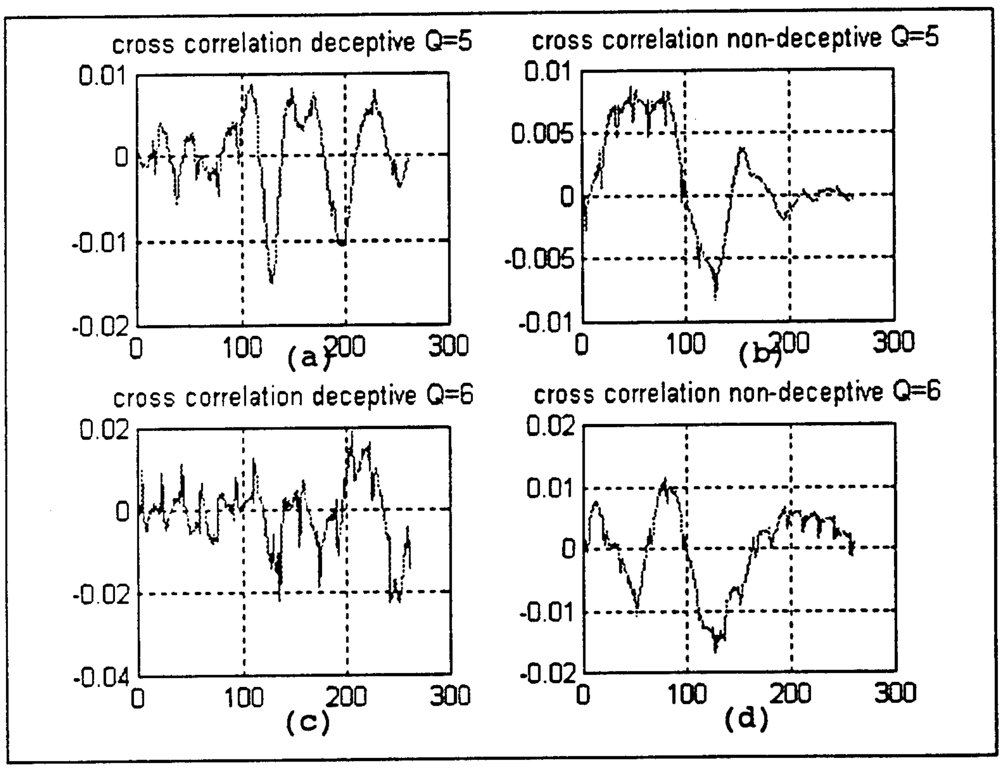


Figure 5. Cross correlation between heart pulse and upper respiratory after modeling for (a) and (b) 90 seconds after relevant question 5. (b) and (c) 90 seconds after control question 6.

3.6 Spectral Analysis

In this section the frequency properties of the polygraph signals such as power spectrum and cross spectral density are analyzed. The cross-correlation and cross spectral density are the tools for examining the relationships between two signals in the time and frequency domains respectively. The power spectrum shows how the variance of the signal is distributed with frequency. The total area underneath the spectrum curve is equal to the variance of the signal. A peak in the spectrum indicates an important contribution to the variance at different frequencies.

The estimated spectrum for different channels were plotted on linear scale in Figure 6 and on logarithmic scale in Figure 7. For spectrum showing large variations in power, a logarithmic scale makes it possible to show more detail over a wide range. However, this exaggerates the visual effects of variations where the spectrum is small. It is often easier to interpret the spectrum plotted on a linear scale than logarithmic scale.

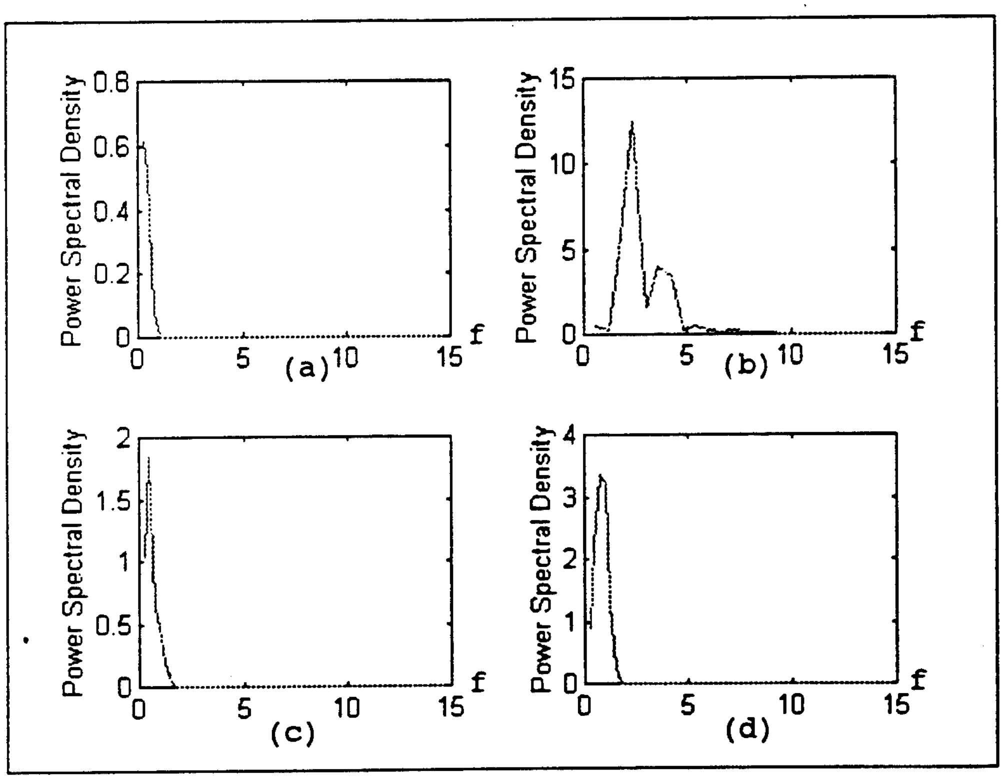


Figure 6. Frequency contents of four polygraph signals on linear scale. (a) GSR for 480 samples, (b) heart pulse for 200 samples, (c) and (d) lower and upper respiratory for 480 samples.

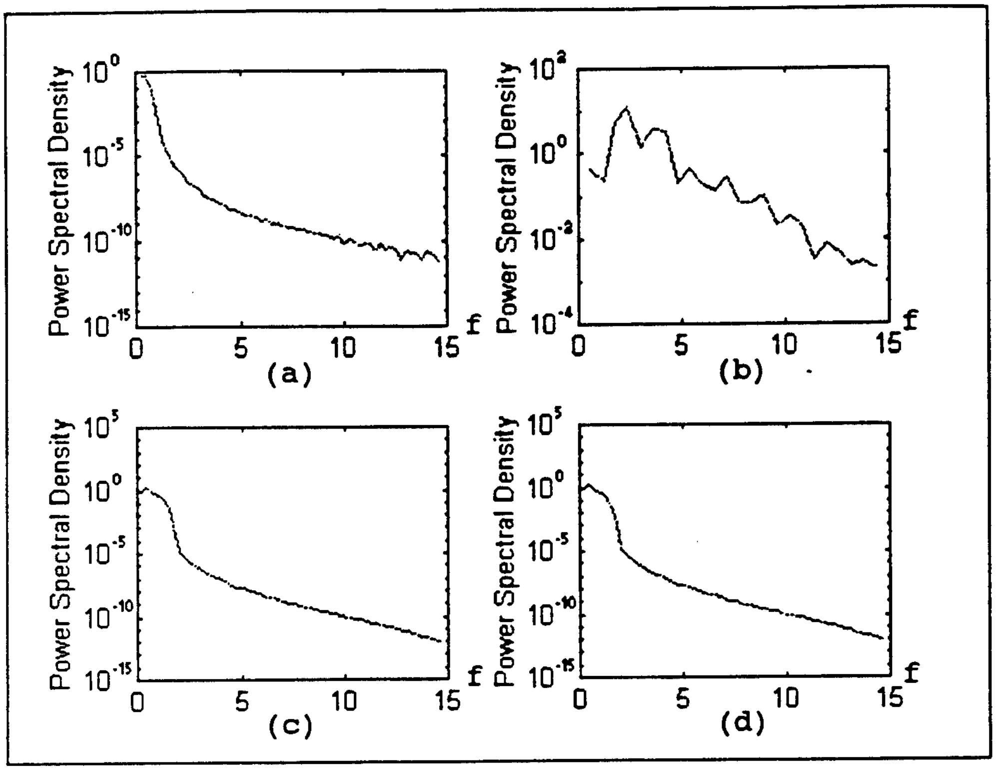


Figure 7. Frequency contents of four polygraph signals on logarithmic scale. (a) GSR for 480 samples, (b) heart pulse for 200 samples, (c) and (d) lower and upper respiratory for 480 samples.

Figure 7 shows for GSR the variance is concentrated at low frequencies indicating a trend or non-stationary behavior. The spectrum for heart pulse signal shows the presence of harmonics with a large peak at fundamental frequency of $f = 2$ Hz and related peaks at 2f, 3f, ...These multiples of the fundamental indicate the non sinusoidal character of the main cyclical component.

The correlation between two signals can be described in the frequency domain by their cross amplitude, phase spectra or the squared coherency. The coherency measures the linear correlation between the two components of the two channels at frequency f. The closer the coherency is to one, the more closely related are the two signals at frequency f.

The MATLAB function *spectrum.m* finds the cross-spectrum and coherency between upper respiratory and electrocardiogram and are shown in Figure 8. Their cross spectrum shows a large peak at $f = 2$ Hz. Maximum cross spectral density and the magnitude of cross spectral density and coherency at fundamental frequency and the second harmonic were considered as features in frequency domain.

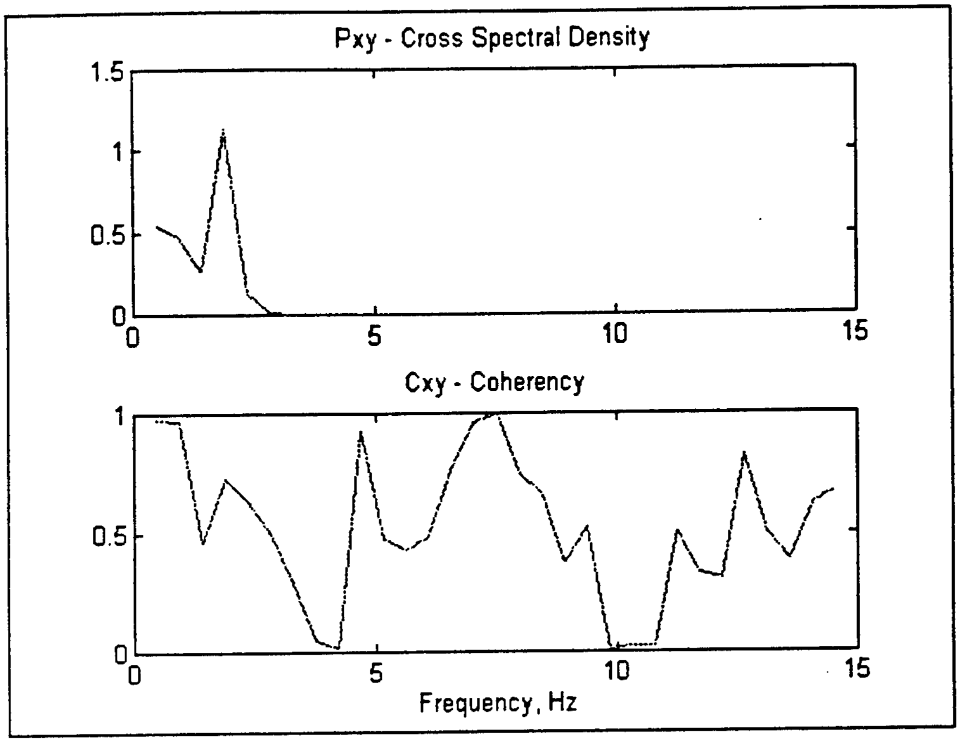


Figure 8. Plots of coherency and cross spectral density between heart pulse and upper respiratory signals.

3.7 Integrated spectral distance

This section describes how to obtain a feature in the frequency domain called integrated spectral difference. This feature was introduced by Martin and Pounds [12]. Other features are calculated separately for each control, relevant and irrelevant questions. The integrated spectral distance is calculated in a different way than the other features. This feature is calculated by taking the difference between the cumulative values of the power spectral density for each relevant and its closest control question. The integrated spectral distance measures the distance between a control and a relevant question directly. Figure 9 shows the cumulative spectral density for a control and a relevant question. The maximum, the frequency where this maximum happens and the area underneath were considered as features.

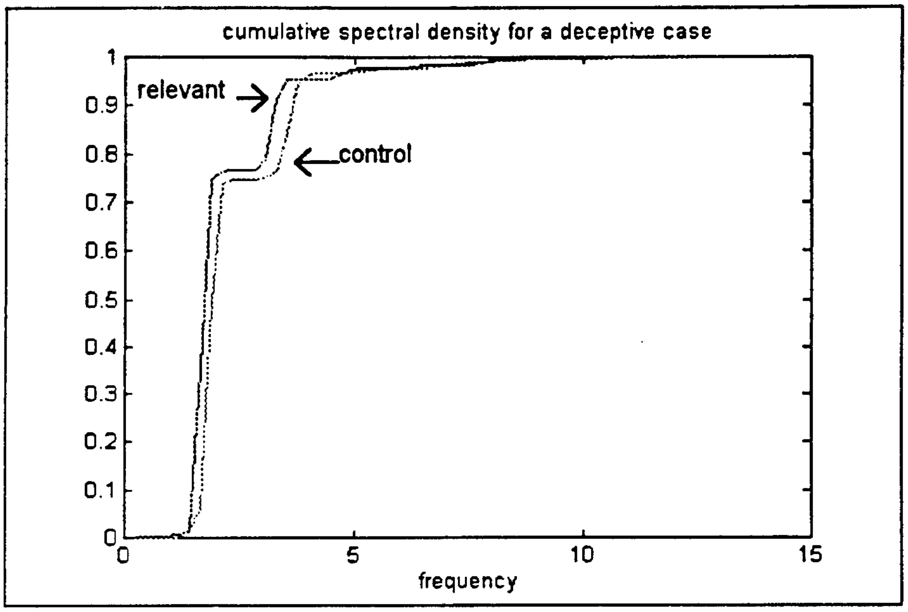


Figure 9. Cumulative integrated spectral density for a control question and relevant question of the heart pulse signal.

3.8 Frequency and Correlation Domain Features

Table 1 summarizes the frequency and correlation features explained in the above sections.

Feature	Channel
Maximum cross correlation	between 2 & 6
Lag of maximum cross correlation	between 2 & 6
Minimum cross correlation	between 2 & 6
Lag of minimum cross correlation	between 2 & 6
Spectral value at fundamental frequency	2
Spectral value at fundamental frequency	6
Spectral value at (fundamental frequency of channel 2) *2	2
Spectral value at (fundamental frequency of channel 6) *2	6
Maximum cross spectral density	between 2 & 6
Coherency at fundamental frequency of channel 2	between 2 & 6
Coherency (at fundamental frequency of channel 2)*2	between 2 & 6
Fundamental frequency	2
Fundamental frequency	5
Maximum or minimum integrated spectral difference	1
Frequency of the maximum integrated spectral difference	1
Area underneath integrated spectral difference	1
maximum or minimum integrated spectral difference	2
Frequency of the maximum integrated spectral difference	2
Area underneath integrated spectral difference	2
Autoregressive parameter	2

Table 1. Frequency and correlation domain features.

4 Feature extraction

4.1 Preprocessing

This chapter explains the steps taken in feature extraction algorithm. In polygraph tests, four physiological responses are measured. These responses are: upper respiratory, lower respiratory, galvanic skin response (GSR) and electrocardiogram. These four polygraph responses are processed into six channels. A low frequency electrocardiogram channel is produced by lowpass filtering the electrocardiogram channel. A high frequency electrocardiogram channel is produced by highpass filtering it. The high frequency electrocardiogram, called heart pulse, the low frequency electrocardiogram, called blood volume and derivative of the low frequency electrocardiogram are used instead of one electrocardiogram channel. To eliminate the noise and any trend, all the signals are filtered and detrended. For more information about the filtering and detrending refer to Jacobs [10].

4.2 Feature Selection

Many of the time domain features were selected based on the examiners' suggestions. However, many of the standard statistical features were also considered as potential features. For more information about time domain features refer to Jacobs [10]. The selected features and the channels which they were extracted from are listed below.

Features	Channel
1) Mean	1 ,2 , 3, 4, 5 , 6
2) Standard deviation	1 ,2 , 3, 4, 5 , 6
3) Minimum	1 ,2 , 3, 4, 5 , 6
4) Maximum	1 ,2 , 3, 4, 5 , 6
5) Curve length	1 ,2 , 3, 4, 5 , 6
6) Mean of derivative	1 ,2 , 3, 4, 5 , 6
7) Median of derivative	1 ,2 , 3, 4, 5 , 6
8) Average amplitude of peaks	2 , 5 , 6
9) Minimum amplitude of peaks	2 , 5 , 6
10) Derivative of amplitudes of peaks	2 , 5 , 6
11) Number of peaks	2 , 5 , 6
12) Minimum subtracted from maximum	1 ,2 , 3, 4, 5 , 6
13) Inhalation/exhalation	5 , 6
14) ratio of inhalation/exhalation before and after a question is asked	5 , 6
15) Fundamental frequency	2, 5
16) Maximum cross correlation	between 2 and 6
17) Lag of maximum cross correlation	between 2 and 6
18) Minimum cross correlation	between 2 and 6
19) Lag of minimum cross correlation	between 2 and 6
20) Spectral value at fundamental frequency	between 2 and 6
21) Spectral value at second harmonic	between 2 and 6
22) Maximum cross spectral density	between 2 and 6
23) Coherency at fundamental frequency	between 2 and 6
24) Coherency at second harmonic	between 2 and 6
25) Autoregressive parameters(AR)	2
26) Maximum or minimum integrated spectral difference (ISD)	1, 2
27) Frequency of maximum ISD	1, 2
28) Area under ISD	1, 2

4.3 Feature Extraction Algorithm

All features are extracted for 10 relevant, irrelevant and control questions except features 26, 27 and 28 that are extracted for each relevant and its closest control question. The program called fextract.m extracts all the basic features for each question on each chart for about 18 non-deceptive and 51 deceptive cases. Due to the small number of non-deceptive cases, each chart for a subject was used as a separate case. By doing this 50 non-deceptive and 150 deceptive files were created.

The test format used in this project is MGQT format. It is a type of control question test in which relevant, irrelevant and control questions are asked in a specific order. Each polygraph test is made of three and in very rare cases four charts for each case. The order in which the questions are asked is changed in the third and fourth charts and sometimes in the second chart. The feature extraction routine needs to have the control, relevant and irrelevant questions labeled. Therefore, for each polygraph chart a complementary chart called question file was created which contains a matrix called Q. The first row of this matrix contains the relevant, the second row the irrelevant and the third row the control questions respectively.

Fragments of each signal are selected before features are extracted. These fragments are shown in Table 2. Start and end points given in the table refer to the time elapsed after the question is asked. A vector of features for each file is created by the program feature.m which is called by fextract.m program. The program first executes all of the processing routines and then extracts the features for each question in the file. The features are extracted for the appropriate time segment (see Table 2) of six channels for each polygraph file. The time segment is created by taking a sample of time series starting several seconds after a question is asked and continuing for a number of seconds.

Channel description	Channel	Start	End
Galvanic Skin conductivity(GSR)	1	2 sec.	14 sec.
High frequency electrocardiogram	2	2 sec.	9 sec.
Low frequency electrocardiogram (LC)	3	2 sec.	18 sec.
Derivative of low frequency electrocardiogram (DLC)	4	0 sec.	8 sec.
Lower Respiratory (LR)	5	2 sec.	18 sec.
Upper Respiratory (UR)	6	2 sec.	18 sec.

Table 2. Time fragment used in feature extraction

The feature extraction algorithm provides a 960 dimensional vector for each file. The features were extracted for the 150 deceptive and 50 non deceptive files and saved in a 960 by 200 matrix called " M". In order to classify subjects using the difference between control and relevant responses, and to make the feature vector smaller, the features were combined according to the following method: for each feature *i* except features 26, 27,28 from each subject *j* compute:

1) The average control responses *AvCij*
2) The average relevant responses *AvRij*
3) The maximum and minimum control responses *MaxCij* and *MinCij*
4) The maximum and minimum relevant responses *MaxRij* and *MinRij*

The feature vector components for feature i are then:

$$1)\, Fij(1) = AvRij - AvCij$$

$$2)\, Fij(2) = \frac{AvRij - AvCij}{AvRij + AvCij}$$

$$3)\, Fij(3) = MaxRij - MaxCij$$

$$4)\, Fij(4) = MinRij - MinCij$$

$$5)\, Fij(5) = MaxRij - MinCij$$

$$6)\, Fij(6) = MinRij - MaxCij$$

$$7)\, Fij(7) = \frac{MaxRij}{MaxCij}$$

For features 26, 27, 28 from each subject *j* compute:

1) The average of relevant-control responses *Av(RC(ij)*
2) The maximum of relevant-control responses *Max(RC(ij)*
3) The minimum of relevant-control responses *Min(RC(ij)*

The feature vector components for feature *i* are then:

$$1)\, F_{ij}(1) = Av\,(RC\,(_{ij}))$$

$$2)\, F_{ij}(2) = Max(RC\,(_{ij}))$$

$$3)\, F_{ij}(3) = Min\,(RC\,(_{ij}))$$

The above procedure is executed by program called *procesf.m* which creates a 669 by 200 dimensional matrix called "F". In order to run the classifier program, the matrix F was divided into three 100 (50 deceptive and 50 non-deceptive) sets of matrices called set1, set2 and set3. These sets are made of 50 non-deceptive cases common in all three sets and three 50 different deceptive sets, called deceptive 1, deceptive 2 and deceptive 3 respectively. The list of the files used in the set1, set2 and set3 are shown in Table 3 in Appendix A.

5 Results

5.1 Frequency Domain Clustering

Classifier is the final stage in a pattern recognition system. The classifier assigns each input to one of the classes. The classifier could be designed after studying the distribution of samples in each class. The KNN classifier was used in this study because of the following:

1) The uncertainty about the shape of deceptive and non deceptive clusters and their sample distributions.
2) The possibility that the samples for one class cluster around more than one point in space.

The frequency domain features did not create a separate distribution of samples for deceptive and non deceptive classes. However, the combination of frequency and time domain features resulted in more distinct clusters. Figure 10 and 11 show the examples of sample distribution (clustering) for non deceptive (x) and deceptive (+) classes.

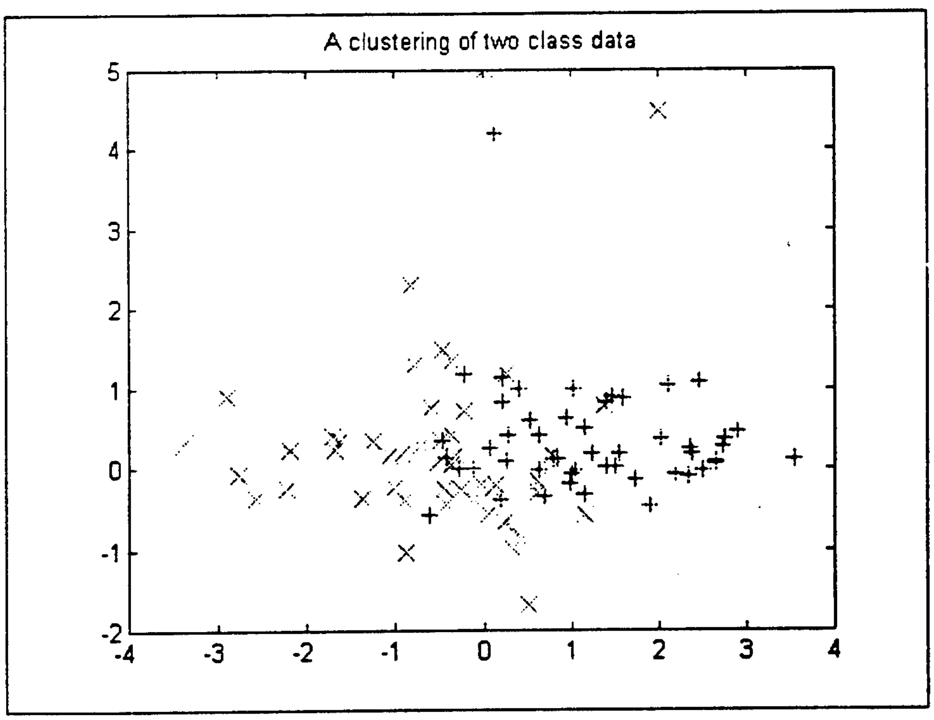


Figure 10. Plot of maximum of GSR versus maximum of Upper Respiratory.

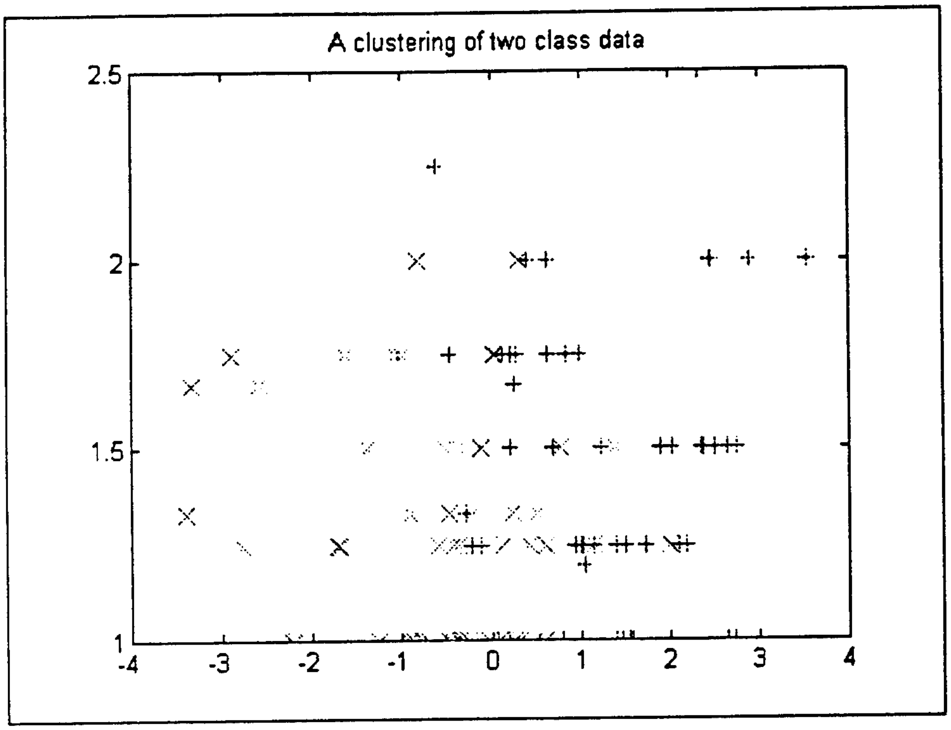


Figure 11. Plot of maximum of GSR versus frequency of maximum integrated spectral difference of GSR.

5.2 Discussion

The 669 features are more than can be used by any classification techniques. Thus, the classification program and the scatter measurement program were run for each feature in each set individually. The results of the first experiment were examined and compared to determine the features which were the best discriminators between deceptive and non-deceptive subjects. After comparing the results, the 30 features with the highest accuracy rate and common in all three sets were selected. These best features were listed in Table 3.

The second experiment used the combination of two features out of the best 30 features. The results for the best 30 features were examined for each set separately. The set3 always had a better performance than the other two sets. However, in order to be consistent, the best features common in all three sets were selected as the 30 best features. More features were added for combination of three and four. The results are shown in Table 4 and 5 in Appendix A.

As it was discussed before, the classifier was used to compare the effectiveness of the single features and to choose the combination of the best features. Changing the classifier parameters such as K might change the results of the classification. However, it is not practical to change all parameters at the same time. Therefore, the classifier was used with the fixed parameters of K=5 and m=2. After selecting the final feature set, theses parameters were changed to find the best classification.

No	feature	Description	Channel	Method
1	10mean	mean	GSR	1
2	10curve	curve length	GSR	2
3	10med_dif	median of the derivative	GSR	1
4	10max_min	minimum subtracted from the maximum	GSR	2
5	10max	maximum of the signal	GSR	1
6	10mdif	mean of derivative	GSR	3
7	20curve	curve length	Heart pulse	1
8	20ampcard	amplitude of the peaks	Heart pulse	1
9	20max_min	minimum subtracted from the maximum	Heart pulse	4
10	20max	maximum of the signal	Heart pulse	4
11	20min	minimum of the signal	Heart pulse	1
12	30med_dif	median of the derivative	Blood pressure	3
13	30max	maximum of the signal	Blood pressure	1
14	40mean	mean	Derivative of Blood pressure	1
15	40max	maximum of the signal	Derivative of Blood pressure	1
16	50curve	curve length	Lower Respiratory	6
17	50ampr	amplitude of the peaks	Lower Respiratory	2
18	50peaknumr	number of the peaks	Lower Respiratory	5
19	50ie	inhalation divided by exhalation	Lower Respiratory	5
20	50max_min	minimum subtracted from the maximum	Lower Respiratory	2
21	50max	maximum of the signal	Lower Respiratory	6
22	60max_min	minimum subtracted from the maximum	Upper Respiratory	2
23	60max	maximum	Upper Respiratory	3
24	10std	standard deviation	GSR	2
25	20std	standard deviation	Heart pulse	1
26	50std	standard deviation	Upper Respiratory	6
27	20armod1	auto regressive parameter	Heart pulse	7
28	26psdcoh1	max cross spectral density	Heart pulse, Lower Respiratory	1
29	10isd1	frequency of maximum integrated spectral difference of control-relevant pair	GSR	1*
30	20isd1	area under integrated spectral difference	Heart pulse	3*

Methods: 1=Difference of Averages, 2=Normalized Average, 3=Max-Max, 4=Min-Min, 5=Max-Min, 6=Min-Max, 7=Max/Min , 1*=Average of relevant-control pairs, 3*=Max of relevant-control pair.

Table 3. 30 best selected Features

Conclusion

The classification results improved consistently by increasing the number of features. The best features are {5 9 21 23} and {5 21 23 29}with 81 and 80 percent correct classification respectively. These features are maximum of GSR(5), difference between maximum and minimum of heart pulse(9), maximum of lower respiratory(21), maximum of upper respiratory(23) and frequency of maximum integrated spectral difference of control-relevant pair for GSR(29).

The best features are simple and obvious features such as maximum and minimum of the polygraph signals. In other words, the features that an examiner can see are the best discriminators between deceptive and non deceptive.

It is important to notice that the best features are the combination of features from all 4 different GSR, heart pulse, lower and upper respiratory. As expected, each subject shows reaction to different channels. Therefore, the combination of all channels is the best representative of deception.

Another point to notice is that the set3 has better classification results than the other two sets. For example, the features {9 14 19 24} and {5 21 23 29}show 87.4 and 86.6 percent correct classification for set3. The data in set3 is made of 50 non deceptive common in all three sets and 50 deceptive cases. This set of deceptive cases, called deceptive 3, are the Acxiton files listed in Table 3 in Appendix A. It is possible that there is some characteristic in these deceptive files that results in better classification.

As stated before, due to the small number of non-deceptive cases available, each chart for a subject was used as a separate case. After classifying the charts, the charts for each case were combined in a way that each case was assigned to the class that the majority of the charts belong to. Using this method, the classification results improved from 81 percent to 85.6 percent for set1 and set2 and from 87 percent to 91 percent for set3. The final result is included in appendix A.

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Appendices

Appendix A

Tables

FILE NAME		FUNDAMENTAL FREQUENCY (Hz) CHANNEL : Heart pulse, WINDOW: 120 S			
QQAV53P6.021	relevant =	1.3636	1.3636	1.3636	1.4286
	control =	1.2500	1.5000		
QQAV53P6.031	relevant =	1.5000	1.3636	1.3043	1.3636
	control =	1.4286	1.3636	1.3636	1.4286
QQBQ4SHI.011	relevant =	2	2	2	2
	control =	2	2		
QQBQ4SHI.021	relevant =	1.7647	1.7647	1.7647	1.8750
	control =	1.8750	1.76		
QQBQ4SHI.031	relevant =	1.7647	1.7647	1.7647	1.7647
	control =	0.8571	1.7647	1.7647	1.6667
QQBSS7WT.011	relevant =	1.5000	1.5000	1.5000	1.3636
	control =	1.5789	1.4286		
QQBSS7WT.021	relevant =	1.5000	1.4286	1.4286	1.4286
	control =	1.5000	1.4286		
QQBSS7WT.031	relevant =	1.4286	1.5000	1.4286	1.3636
	control =	1.4286	1.5000	1.4286	1.5000

Table 1. Fundamental frequency for non-deceptive files for 120 seconds for heart pulse.

FILE NAME	FUNDAMENTAL FREQUENCY(Hz) CHANNEL : CARDIO, WINDOW: 120 S				
QQ9SOW8L.021	relevant =	1.7647	1.6667	1.5789	1.6667
	control =	1.5789	1.5789		
QQ9SOW8L.031	relevant=	1.5789	1.5789	1.6667	1.6667
	control =	1.8750	1.6667	1.7647	1.5789
QQ9SQIK9.011	relevant =	1.5789	1.5000	1.5000	1.5789
	control =	1.5789	1.5000		
QQ9SQIK9.021	relevant =	1.3043	1.5789	1.5789	1.4286
	control =	1.5789	1.5789		
QQ9SQIK9.031	relevant =	1.5000	1.5000	1.6667	
	control =	1.4286	1.2000	1.5789	1.5789
QQ9W0B9F.011	relevant =	1.5000	1.4286	1.5000	1.5000
	control =	1.4286	1.5789		
QQ9W0B9F.031	relevant=	1.4286	1.5000	1.4286	1.4286
	control =	1.5000	1.4286		
QQ9W0B9F.041	relevant =	1.4286	1.3636	1.4286	1.5000
	control =	1.4286	1.3636		
QQ9U4FMU.011	relevant =	1.5789	1.6667	1.6667	1.6667
	control =	1.6667	1.5789		

Table 2. Fundamental frequency for deceptive files for 120 seconds for heart pulse.

Non deceptive	Deceptive 1	Deceptive 2	Deceptive 3
QQ8R9OIO.011	QQ4Q1O83.011	QQ7LX5Q0.021	QQ8RAJ0C.011
QQ8R9OIO.021	QQ4Q1O83.021	QQ7LX5Q0.031	QQ8RAJ0C.021
QQ8R9OIO.031	QQ4Q1O83.031	QQ7MN2Y0.011	QQ8RAJ0C.031
QQ95LU1T.011	QQ4Q3MDC.011	QQ7MN2Y0.021	QQ9EUKVT.011
QQ95LU1T.021	QQ4Q3MDC.021	QQ7MN2Y0.031	QQ9EUKVT.021
QQ95LU1T.031	QQ4Q3MDC.031	QQ7TC5UF.011	QQ9EUKVT.031
QQAURNUS.021	QQ51DE36.011	QQ7TC5UF.021	QQ9IOOXO.021
QQAURNUS.031	QQ51DE36.021	QQ7TC5UF.031	QQ9IOOXO.041
QQAV53P6.011	QQ51DE36.041	QQ7TQVER.011	QQ9SOW8L.011
QQAV53P6.021	QQ6RQGH6.011	QQ7TQVER.021	QQ9SOW8L.021
QQAV53P6.031	QQ6RQGH6.021	QQ7TQVER.031	QQ9SOW8L.031
QQBQ4SHI.011	QQ6RQGH6.031	QQ7TVADC.011	QQ9SQIK9.011
QQBQ4SHI.021	QQ6RQGH6.041	QQ7TVADC.021	QQ9SQIK9.021
QQBQ4SHI.031	QQ6T711O.011	QQ7TVADC.031	QQ9SQIK9.031
QQBSS7WT.011	QQ6T711O.021	QQ7U2T4R.011	QQ9W0B9F.011
QQBSS7WT.021	QQ6T711O.031	QQ7U2T4R.021	QQ9W0B9F.031
QQBSS7WT.031	QQ6Z59IG.011	QQ7U2T4R.031	QQ9W0B9F.041
QQ7OXM60.021	QQ6Z59IG.021	QQ7YP7QU.011	QQ9U4FMU.011
QQ7RH0RO.011	QQ6Z59IG.031	QQ7YP7QU.021	QQ9U4FMU.021
QQ7RH0RO.021	QQ7PP9B9.011	QQ7YP7QU.031	QQ9U4FMU.031
QQ7RH0RO.031	QQ7PP9B9.021	QQ7YZOJ3.011	QQ9Y_SVF.011
QQ7R51P9.011	QQ7PP9B9.031	QQ7YZOJ3.021	QQ9Y_SVF.021
QQ7R51P9.021	QQ7PDU1X.011	QQ7YZOJ3.031	QQ9Y_SVF.031
QQ7R51P9.031	QQ7PDU1X.021	QQ8_0DPT.011	QQ9YH3QF.011
QQ9TDSP3.011	QQ7PDU1X.031	QQ8_0DPT.021	QQ9YH3QF.021
QQ9TDSP3.021	QQ7_PIPF.011	QQ8_0DPT.031	QQ9YH3QF.031
QQ9TDSP3.031	QQ7_PIPF.021	QQ8_0DPT.041	QQA2TT4C.011
QQA8OWOI.011	QQ7_PIPF.031	QQ8_2UQ9.011	QQA2TT4C.021
QQA8OWOI.021	QQ7_JT70.011	QQ8_2UQ9.021	QQA2TT4C.031
QQA8OWOI.031	QQ7_JT70.021	QQ8_2UQ9.031	QQA3HIRX.011
QQBT22O6.011	QQ7_JT70.031	QQ800IG6.011	QQA3HIRX.021
QQBT22O6.021	QQ738DYX.011	QQ800IG6.021	QQA3HIRX.031
QQBT22O6.031	QQ738DYX.021	QQ800IG6.031	QQA32UTF.011
QQBO9O_9.011	QQ738DYX.031	QQ82OIU9.011	QQA32UTF.021
QQBO9O_9.021	QQ75ULP9.011	QQ82OIU9.021	QQA32UTF.031
QQBO9O_9.031	QQ75ULP9.021	QQ82OIU9.031	QQA6U_IF.011
QQBC7PP6.011	QQ75ULP9.031	QQ82SUTX.011	QQA6U_IF.031
QQBC7PP6.021	QQ79_EYF.011	QQ82SUTX.021	QQA6U_IF.041
QQBC7PP6.031	QQ79_EYF.021	QQ82SUTX.031	QQAM4E3L.011
QQCHCK_O.011	QQ79_EYF.031	QQ860ZNU.011	QQAM4E3L.021
QQCHCK_O.021	QQ7BGDML.011	QQ860ZNU.021	QQAM4E3L.031
QQCHCK_O.031	QQ7BGDML.021	QQ860ZNU.031	QQARF2_X.011
QQCDTKP0.011	QQ7BGDML.031	QQ89U_ZR.011	QQARF2_X.021
QQCDTKP0.031	QQ7ETC8I.011	QQ89U_ZR.021	QQARF2_X.031
QQCDTKP0.041	QQ7ETC8I.021	QQ89U_ZR.031	QQAWA38X.011
QQCM5Y56.011	QQ7ETC8I.031	QQ8ATU26.011	QQAWA38X.021
QQCQQT8Y.011	QQ7JAQCS.011	QQ8ATU26.021	QQAWA38X.031
QQCQQT8Y.021	QQ7JAQCS.021	QQ8ATU26.031	QQAYXZGU.011
QQCQQT8Y.031	QQ7JAQCS.031	QQ8FGMVI.011	QQAYXZGU.021
QQCQQT8Y.041	QQ7LX5Q0.011	QQ8FGMVI.021	QQAYXZGU.031

Table 3. List of files used in this experiment. 50 non-deceptive cases and 50 deceptive cases from set1, set2 and set3 are listed in column 1 through 4 respective

Set	Features			accuracy
Set1	10	21	26	79.4
	5	11	23	77.6
	5	21	23	77.4
Set2	12	20	24	79.8
	19	24	30	78.6
	5	21	23	77.4
Set3	9	19	24	85.2
	5	23	29	82.4
	5	21	23	81.2
Average	5	23	29	78.2
	5	7	23	77.6
	5	21	23	77.3

Table 4. The three best features of combination of 3 for each set and their average.

Set	Features				accuracy
Set1	5	9	21	23	81.0
	5	11	21	23	80.2
	5	21	23	29	74.4
Set2	5	14	23	29	81.0
	5	9	21	23	79.4
	5	21	23	29	79.0
Set3	9	14	19	24	87.4
	5	21	23	29	86.6
	5	21	23	9	82.5
Average	5	9	21	23	81.0
	5	21	23	29	80.0
	5	21	23	11	79.8

Table 5. The three best features of combination 4 for each set and their average.

File	Membership	Defuzzified	Result
1.0000	0.2736	0	
2.0000	0.3339	0	
3.0000	0.5397	0	0
4.0000	0.5450	0	
5.0000	0.7423	1.0000	
6.0000	0.1732	0	0
7.0000	0.8901	1.0000	
8.0000	1.0000	1.0000	1 Misclassified
9.0000	0.5376	0	
10.0000	0.1742	0	
11.0000	0.4366	0	0
12.0000	0.3458	0	
13.0000	0.5145	0	
14.0000	0.5178	0	0
15.0000	0.1016	0	
16.0000	0	0	
17.0000	0	0	0
18.0000	0.1334	0	0
19.0000	0	0	
20.0000	0	0	
21.0000	0.2923	0	0
22.0000	0	0	
23.0000	0	0	
24.0000	0.1607	0	0
25.0000	0	0	
26.0000	0.4421	0	
27.0000	1.0000	1.0000	0
28.0000	0.3307	0	
29.0000	0.0583	0	
30.0000	0.4965	0	0
31.0000	0.3505	0	
32.0000	0.1181	0	
33.0000	0.2101	0	0

Table 6. Classification of the files in Set1.

File	Membership	Defuzzified	Result
34.0000	0.5970	0	
35.0000	0	0	
36.0000	0.1193	0	0
37.0000	0.3174	0	
38.0000	0.8117	1.0000	
39.0000	0.0997	0	0
40.0000	0.1889	0	
41.0000	0.4215	0	
42.0000	0.1635	0	0
43.0000	0.6474	1.0000	
44.0000	0	0	
45.0000	0.5495	0	0
46.0000	0.1115	0	0
47.0000	0	0	
48.0000	0.3986	0	
49.0000	0	0	
50.0000	0	0	0
51.0000	0.6709	1.0000	
52.0000	1.0000	1.0000	
53.0000	0.5297	0	1
54.0000	0.7245	1.0000	
55.0000	0.9200	1.0000	
56.0000	1.0000	1.0000	1
57.0000	0.9105	1.0000	
58.0000	0.9398	1.0000	
59.0000	0.5657	0	1
60.0000	0.8968	1.0000	
61.0000	1.0000	1.0000	
62.0000	0.2793	0	
63.0000	0.1088	0	0 Misclassified
64.0000	0.6245	1.0000	
65.0000	0.8643	1.0000	
66.0000	0.5054	0	1

Table 6. Continued.

File	Membership	Defuzzified	Result
67.0000	0.8498	1.0000	
68.0000	0.6969	1.0000	
69.0000	0.8397	1.0000	1
70.0000	0.2901	0	
71.0000	0.8291	1.0000	
72.0000	0.3982	0	0 Misclassified
73.0000	1.0000	1.0000	
74.0000	0.2463	0	
75.0000	0.8043	1.0000	1
76.0000	0.6676	1.0000	
77.0000	1.0000	1.0000	
78.0000	1.0000	1.0000	1
79.0000	1.0000	1.0000	
80.0000	0.7538	1.0000	
81.0000	1.0000	1.0000	1
82.0000	1.0000	1.0000	
83.0000	0.8378	1.0000	
84.0000	1.0000	1.0000	1
85.0000	0.8926	1.0000	
86.0000	0.5448	0	
87.0000	0.5751	0	0 Misclassified
88.0000	0.8273	1.0000	
89.0000	0.2945	0	
90.0000	0.9110	1.0000	1
91.0000	1.0000	1.0000	
92.0000	1.0000	1.0000	
93.0000	0	0	1
94.0000	0.2887	0	
95.0000	0.2079	0	
96.0000	0.5793	0	0 Misclassified
97.0000	1.0000	1.0000	
98.0000	0.7971	1.0000	
99.0000	0.8708	1.0000	1
100.0000	1.0000	1.0000	1

Table 6. Continued.

File	Membership	Defuzzified	Result
1.0000	0.2579	0	
2.0000	0.1307	0	
3.0000	0	0	0
4.0000	0.2652	0	
5.0000	0.4345	0	
6.0000	0.1175	0	0
7.0000	1.0000	1.0000	
8.0000	0.7086	1.0000	1 Misclassified
9.0000	0.2856	0	
10.0000	0.2745	0	
11.0000	0.3056	0	0
12.0000	0.2720	0	
13.0000	0.5019	0	
14.0000	0.8871	1.0000	0
15.0000	0.0912	0	
16.0000	0	0	
17.0000	0	0	0
18.0000	0.8334	1.0000	1 Misclassified
19.0000	0	0	
20.0000	0	0	
21.0000	0.5483	0	0
22.0000	0	0	
23.0000	0	0	
24.0000	0.1535	0	0
25.0000	0.4955	0	
26.0000	0.1013	0	
27.0000	1.0000	1.0000	0
28.0000	0.3788	0	
29.0000	0.1638	0	
30.0000	0.0905	0	0
31.0000	0	0	
32.0000	0.1431	0	
33.0000	0.0937	0	0

Table 7. Classification of the files in set2.

File	Membership	Defuzzified	Result
34.0000	0	0	
35.0000	0	0	
36.0000	0.1281	0	0
37.0000	0.3690	0	
38.0000	0.5734	0	
39.0000	0.1569	0	0
40.0000	0.3659	0	
41.0000	0.4124	0	
42.0000	0.1704	0	0
43.0000	0.4251	0	
44.0000	0.0664	0	
45.0000	0.5356	0	0
46.0000	0.5084	0	0
47.0000	0.1735	0	
48.0000	0.7512	1.0000	
49.0000	0.5115	0	
50.0000	0.0976	0	0
51.0000	0.6361	1.0000	
52.0000	0.8482	1.0000	1
53.0000	0.3471	0	
54.0000	0.8822	1.0000	
55.0000	1.0000	1.0000	1
56.0000	1.0000	1.0000	
57.0000	1.0000	1.0000	
58.0000	0.8730	1.0000	1
59.0000	0	0	
60.0000	0.0389	0	
61.0000	0.3643	0	0 Misclassified
62.0000	1.0000	1.0000	
63.0000	0.8174	1.0000	
64.0000	0.8875	1.0000	1
65.0000	0.7995	1.0000	
66.0000	0.5919	0	
67.0000	0.7533	1.0000	1

Table 7. Continued.

File	Membership	Defuzzified	Result
68.0000	0.7337	1.0000	
69.0000	0.8524	1.0000	
70.0000	0.8602	1.0000	1
71.0000	0.2217	0	
72.0000	1.0000	1.0000	
73.0000	0.1268	0	0 Misclassified
74.0000	0.8860	1.0000	
75.0000	0.2121	0	
76.0000	0.1684	0	
77.0000	0.6903	1.0000	0 Misclassified
78.0000	0.7680	1.0000	
79.0000	0.8735	1.0000	
80.0000	0.8013	1.0000	1
81.0000	0.1748	0	
82.0000	0.5428	0	
83.0000	0.8496	1.0000	0 Misclassified
84.0000	0.3444	0	
85.0000	0.8298	1.0000	
86.0000	0.8590	1.0000	1
87.0000	0.6879	1.0000	
88.0000	0.9082	1.0000	
89.0000	0.6653	1.0000	1
90.0000	0.1636	0	
91.0000	0.8754	1.0000	
92.0000	0.8594	1.0000	1
93.0000	0.5185	0	
94.0000	0.4932	0	
95.0000	0.7802	1.0000	0 Misclassified
96.0000	0.8684	1.0000	
97.0000	0.8788	1.0000	
98.0000	1.0000	1.0000	1
99.0000	1.0000	1.0000	
100.0000	0.8669	1.0000	1

Table 7. Continued.

File	Membership	Defuzzified	Result
1.0000	0.3986	0	
2.0000	0.2845	0	
3.0000	0.2562	0	0
4.0000	0.2786	0	
5.0000	0.3226	0	
6.0000	0	0	0
7.0000	1.0000	1.0000	
8.0000	0.5055	0	
9.0000	0.1434	0	0
10.0000	0	0	
11.0000	0	0	0
12.0000	0.0691	0	
13.0000	0.4744	0	
14.0000	0.4708	0	0
15.0000	0	0	
16.0000	0	0	
17.0000	0	0	0
18.0000	0.4623	0	0
19.0000	0	0	
20.0000	0	0	
21.0000	0.2096	0	0
22.0000	0	0	
23.0000	0	0	
24.0000	0.0516	0	0
25.0000	0.2885	0	
26.0000	0.0981	0	
27.0000	0.9336	1.0000	0
28.0000	0.2254	0	
29.0000	0.1465	0	
30.0000	0.0680	0	0
31.0000	0	0	
32.0000	0	0	
33.0000	0.0939	0	0

Table 8. Classification of the files in Set3.

File	Membership	Defuzzified	Result
34.0000	0.3917	0	
35.0000	0	0	
36.0000	0	0	0
37.0000	0.1689	0	
38.0000	0.5220	0	
39.0000	0	0	0
40.0000	0.0969	0	
41.0000	0	0	
42.0000	0	0	0
43.0000	0.4810	0	
44.0000	0.3154	0	
45.0000	0.4552	0	0
46.0000	0.3285	0	0
47.0000	0.3690	0	
48.0000	0.5593	0	
49.0000	0.3522	0	
50.0000	0.2325	0	0
51.0000	1.0000	1.0000	
52.0000	0.9052	1.0000	
53.0000	0.8115	1.0000	1
54.0000	0.8397	1.0000	
55.0000	0.8754	1.0000	
56.0000	0.0930	0	1
57.0000	0.8330	1.0000	
58.0000	1.0000	1.0000	1
59.0000	1.0000	1.0000	
60.0000	1.0000	1.0000	
61.0000	1.0000	1.0000	1
62.0000	1.0000	1.0000	
63.0000	0.6496	1.0000	
64.0000	0.5075	0	1
65.0000	0.0823	0	
66.0000	0.7810	1.0000	
67.0000	0.2356	0	0 Misclassified

Table 8. Continued.

File	Membership	Defuzzified	Result
68.0000	1.0000	1.0000	
69.0000	1.0000	1.0000	
70.0000	1.0000	1.0000	1
71.0000	1.0000	1.0000	
72.0000	1.0000	1.0000	
73.0000	1.0000	1.0000	1
74.0000	1.0000	1.0000	
75.0000	1.0000	1.0000	
76.0000	1.0000	1.0000	1
77.0000	1.0000	1.0000	
78.0000	1.0000	1.0000	
79.0000	1.0000	1.0000	1
80.0000	0.6068	1.0000	
81.0000	0.9054	1.0000	
82.0000	0.4134	0	1
83.0000	1.0000	1.0000	
84.0000	0	0	
85.0000	0.2914	0	0 Misclassified
86.0000	1.0000	1.0000	
87.0000	1.0000	1.0000	
88.0000	0.8786	1.0000	1
89.0000	0.9018	1.0000	
90.0000	1.0000	1.0000	
91.0000	1.0000	1.0000	1
92.0000	1.0000	1.0000	
93.0000	0.9135	1.0000	
94.0000	0.8292	1.0000	1
95.0000	0.7423	1.0000	
96.0000	1.0000	1.0000	
97.0000	0.0902	0	1
98.0000	0.2564	0	
99.0000	0	0	
100.0000	0.4387	0	0 Misclassified

Table 8. Continued.

Appendix B

Programs

```
function v=armod(var,M)

% This function finds the autoregressive parameter fo the signal
% and then prewhitens the signal using the prewhiten filter.
% Recursive Levinston and durbin algorithm is used to find the AR parameters

% To use the function the user should enter the signal and the AR model order
% eg armod(variable, model order)

Fs=30;                                    %sampling frequency


r=xcorr(var,'biased');                    %rx(0) is at index K
K=length(var);
rx=r(K:K+M+1);                            %rx(0),rx(1),..rx(M)


% Estimate the reflection coefficients

a(1,1)=1;
P=rx(1);

for k=0:M-1
   accum=0;
   for m=0:k
      accum=accum+a(k+1,m+1)*rx(k-m+2);
   end
   gamma(k+2)=-accum/P;
   P=P*(1-abs(gamma(k+2))^2);
   a(k+2,1)=1;
   a(k+2,k+2)=gamma(k+2);
   for m=1:k
      a(k+2,m+1)=a(k+1,m+1)+gamma(k+2)*a(k+1,k-m+2);
   end
end
parameter=a(M+1,:);

bb=[1];
aa=a(M+1,:);

v=filter(aa,bb,var);
```

```
function  freq=fundfreq(frag)

% This function called fundfreq (stands for fundamental frequency)
% finds the fundamental frequency of the desired signal.
% for the K interval of a question using autocorrelation function.
% For a periodic signal with the period p, the autocorrelation function
% attains a maximum at 0,p,2p,..
% regardless of the time origin of the signal, the period can be estimated
% by finding the location the first maximum in the autocorrelation function.


%For using this function the user should enter the file segment fundfreq(frag).


Fs = 30;                                %Sampling frequency
K=length(frag);

y = xcorr(frag);                        % finds the autocorralation function

q = diff(abs(y(K:2*K-1)));              % differentiates the variable

z = q>0;                                % z = 1 if q is greater than 0

f = diff(z);                            %finds the indices where the 2nd derivative
                                        %is -1 or +1 which indicates peaks and valleys

peak = find(f<0);                       %finds the peak indices


m =K+peak;
[i,j]=max(abs(y(m)));                   %finds the maximum peak value and its index

lofreq =find(f>=0);
   if length(lofreq)==length(f)
     freq=0;
   else
     freq = Fs/peak(j);
   end
```

```
function y=croscor(var1,var2)


% This function finds the cross correlation between two variables
% The first variable is prewhitened first by calling
% armod (stands for AR modeling) program.
% The function returns maximum and minimum of the croscorrelation
% and the lag that these maximum and minimum happen.
%To use this command the user must enter the two
%variable names to be correlated.
%
% eg.   croscor(variable1,variable2)

K=min(length(var1),length(var2));



M=10;                                                % Model order
v1=armod(var1,M);

yd= xcorr(v1(20:K),var2(20:K),'biased');

[maximum lagmax]=max(real(yd));

[minimum lagmin]=min(real(yd));

y=[maximum lagmax minimum lagmin];
```

```
function feature= feature(file_name,relevant,irrelevant,control,features,offset,CR_feature)

% This function produces a feature vector for a given file
% Relevent, irrelevent, and control are vectors which contain
% the questions these features are extracted from.
%
% eg. featurev(t79,[3 5],[1 4], [6 10],feature_list)

% The above example gives the features for
% the file t79 of the 3rd and 5th question which are relevent in this
% MGQT format, the 1st and 4th question which are irrelevent
% and the 6th and 10th questions which are control

% feature_list=['10mean(frag ) ';
%             '20curve(frag )';
%             '30area(frag ) '];


feature_list = features;



% The channels are ordered as follows:
% 1:GSR, 2:HiCardio, 3:LowCardio, 4:DerLowCardio, 5:LowResp, 6:UpResp


% This is a matrix of the time delay after asking a question to start of extracting
% the feature, and finish extracting the feature for each channel.

Times=[
        2, 14;
        3, 9 ;
        3, 18;
        1, 8 ;
        2, 18;
        2, 18];

% These are preprocessing functions.
Preprocess=[  'detgsr';
              'dethic';
              'detlc ';
              'dercd ';
              'detlr ';
              'detur '];
```

```
data=zeros(6,length(file_name(:,5)));
% Standardize and detrend the channels and derive new channels

for i=1:6,
        data(i,:)=eval([Preprocess(i,:),'(file_name)'])';
end


marker = file_name(:,5);    % 0 begin test and end test
                            % 0 examiner begins asking question
                            % 1 examiner finishes asking question
                            % 2 subject begins response to question
                            % 9 does not mark an event

begin = find(marker == 0);      % finds indecies where marker = 0 (question begins)
begin=begin(2:length(begin)); % elliminates the marker at the beginning of the test

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
++++++++++++++
% This for loop creates feature vectors for each relevant quesion
%
% eg x = [mean(gsr),std(gsr),area(gsr),mean(lr),std(lr),area(lr),etc.........
% curve length,amplitude of peaks,# of peaks]
%++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
++++++++++++++++++

feature_count=1;

for i = 1:max(find(relevant~=0)),
        question=relevant(i);

        for j=1:length(feature_list(:,1))
                        channel_number=eval(feature_list(j,1));
                        second_channel=eval(feature_list(j,2));
                        st=begin(question)+30*Times(channel_number,1);
                        fn=begin(question)+30*Times(channel_number,2);
                        st2=begin(question)-30*Times(channel_number,2);
                        fn2=begin(question)-30*Times(channel_number,1);
                        fr=feature_list(j,3:length(feature_list(1,:)));
                        frag=data(channel_number,st:fn);
                        frag2 = data(channel_number,st2:fn2);
                        if second_channel ~= 0
```

```
                st3=begin(question)+30*Times(second_channel,1);
                fn3=begin(question)+30*Times(second_channel,2);
                frag3 = data(second_channel,st3:fn3);
            end
            tempy=eval(fr);
            for m = 1:length(tempy)
                x(feature_count) = tempy(m);
                feature_count=feature_count+1;
            end
    end
end
%------------------------------------------------------------------
% Irrelevant questions

feature_count=1;

for i = 1:(max(find(irrelevant~=0))-offset)
    question=irrelevant(i);
    for j=1:length(feature_list(:,1))
        channel_number=eval(feature_list(j,1));
        second_channel=eval(feature_list(j,2));
        st=begin(question)+30*Times(channel_number,1);
        fn=begin(question)+30*Times(channel_number,2);
        st2=begin(question)-30*Times(channel_number,2);
        fn2=begin(question)-30*Times(channel_number,1);
        fr=feature_list(j,3:length(feature_list(1,:)));
        frag=data(channel_number,st:fn);
        frag2 = data(channel_number,st2:fn2);
        if second_channel ~= 0
            st3=begin(question)+30*Times(second_channel,1);
            fn3=begin(question)+30*Times(second_channel,2);
            frag3 = data(second_channel,st3:fn3);
        end
        tempy=eval(fr);
        for m = 1:length(tempy)
            y(feature_count) = tempy(m);
            feature_count=feature_count+1;
        end
    end
end
```

```
%-------------------------------------------------------------------
% Control questions

feature_count=1;

for i = 1:max(find(control~=0)),
        question=control(i);

        for j=1:length(feature_list(:,1))
                channel_number=eval(feature_list(j,1));
                second_channel=eval(feature_list(j,2));
                st=begin(question)+30*Times(channel_number,1);
                fn=begin(question)+30*Times(channel_number,2);
                st2=begin(question)-30*Times(channel_number,2);
                fn2=begin(question)-30*Times(channel_number,1);
                fr=feature_list(j,3:length(feature_list(1,:)));
                frag=data(channel_number,st:fn);
                frag2 = data(channel_number,st2:fn2);
                if second_channel ~= 0
                        st3=begin(question)+30*Times(second_channel,1);
                        fn3=begin(question)+30*Times(second_channel,2);
                        frag3 = data(second_channel,st3:fn3);
                end
                tempy=eval(fr);
                for m = 1:length(tempy)
                        z(feature_count) = tempy(m);
                        feature_count=feature_count+1;
                end
        end
end
%-------------------------------------------------------------------------------------

% control & relevant


feature_count=1;

for i = 1:max(find(relevant~=0)),
                for k=1:max(find(control~=0)),
                        q(k)=abs(relevant(i)-control(k));
                end

                [a b]=min(q);
```

```
            question1=relevant(i);
            question2=control(b);

            for j=1:length(CR_feature(:,1))
                channel_number=eval(CR_feature(j,1));
                st=begin(question1)+30*Times(channel_number,1);
                fn=begin(question1)+30*Times(channel_number,2);
                st2=begin(question2)+30*Times(channel_number,1);
                fn2=begin(question2)+30*Times(channel_number,2);
                fr=CR_feature(j,3:length(CR_feature(1,:)));
                frag1=data(channel_number,st:fn);
                frag2=data(channel_number,st2:fn2);
                tempy=eval(fr);
                for m = 1:length(tempy)
                    w(feature_count) = tempy(m);
                    feature_count=feature_count+1;
                end
            end
end

feature=[x,y,z,w]';
```

```
function   isd_dif=isd(frag1,frag2)

% This is a integrated  spectral difference(isd) function that finds the cumulativespectral
% density of a control-relevant pair, then calculates the difference between the
% isd of control and the relevant for a part of a question.
% This function returns the max or min and the frequency (points)
% where this max or min happens and the area underneath  this difference.

% To use this command the user must enter the two variable names.
% The first variable is a control question fragment and the second is
% a relevant question fragment.
% eg.  isd1(variable1,variable2)

Fs = 30;
K=min(length(frag1),length(frag2));

nnp =1;
np = 2^nnp;
L = K/np;
L=2^(nextpow2(L));

M= spectrum (frag1,L);          %spectral density of the first (control) question
N= spectrum (frag2,L);          %spectral density of the second(relevant) question

pqc = cumsum(M(:,1));           %Cumulative sum of the integrated spectral density
pqr = cumsum(N(:,1));           %Cumulative sum of the integrated spectral density

clear M
clear N
hc = pqc/pqc(L/2);
hr = pqr/pqr(L/2);

CR_dif= hr' - hc';
 if (abs(max(CR_dif))>abs(min(CR_dif)))
    [CR_dif, mpoint]=max(CR_dif);
 else
    [CR_dif ,mpoint]=min(CR_dif);
 end
isd_dif=[ CR_dif  mpoint trapz(hr'-hc')];
```

```
feature_list=[  '10mean(frag)          ';
                '10curve(frag)         ';
                '10area(frag)          ';
                '10med_dif(frag,8)     ';
                '10max_min(frag)       ';
                '10max(frag)           ';
                '10min(frag)           ';
                '10mdif(frag)          ';
                '20mean(frag)          ';
                '20curve(frag)         ';
                '20area(frag)          ';
                '20ampcard(frag)       ';
                '20dampcard(frag)      ';
                '20peaknumc(frag)      ';
                '20med_dif(frag,5)     ';
                '20max_min(frag)       ';
                '20max(frag)           ';
                '30min(frag)           ';
                '20min(frag)           ';
                '20mdif(frag)          ';
                '20minampc(frag)       ';
                '30mean(frag)          ';
                '30curve(frag)         ';
                '30area(frag)          ';
                '30med_dif(frag,5)     ';
                '30max_min(frag)       ';
                '30max(frag)           ';
                '30mdif(frag)          ';
                '40mean(frag)          ';
                '40min(frag)           ';
                '40mdif(frag)          ';
                '40curve(frag)         ';
                '40area(frag)          ';
                '40med_dif(frag,5)     ';
                '40max_min(frag)       ';
                '40max(frag)           ';
                '50mean(frag)          ';
                '50curve(frag)         ';
                '50area(frag)          ';
                '50ampr(frag)          ';
                '50peaknumr(frag)      ';
                '50ie(frag)            ';
                '50dampr(frag)         ';
                '50ieie(frag, frag2)   ';
                '50med_dif(frag,8)     ';
                '50max_min(frag)       ';
                '50max(frag)           ';
                '50min(frag)           ';
                '50mdif(frag)          ';
                '50minampr(frag)       ';
                '60mean(frag)          ';
```

```
                    '60curve(frag)            ';
                    '60area(frag)             ';
                    '60ampr(frag)             ';
                    '60dampr(frag)            ';
                    '60peaknumr(frag)         ';
                    '60ie(frag)               ';
                    '60ieie(frag, frag2)      ';
                    '60med_dif(frag,8)        ';
                    '60max_min(frag)          ';
                    '60max(frag)              ';
                    '60min(frag)              ';
                    '60mdif(frag)             ';
                    '60minampr(frag)          ';
                    '10std(frag)              ';
                    '20std(frag)              ';
                    '30std(frag)              ';
                    '40std(frag)              ';
                    '50std(frag)              ';
                    '60std(frag)              ';
                    '20armod1(frag)           ';
                    '20cor1(frag)             ';
                    '50cor1(frag)             ';
                    '26croscor(frag,frag3)    ';
                    '26psdcoh1(frag,frag3)    '];

CR_feature=[
                    '10isd1(frag1,frag2)          ';
                    '20isd1(frag1,frag2)          '];


lf=length(feature_list(:,1));
cd \mgqt\g1
files1
for d=1:3
        if d==2
                cd \mgqt\g2
                files2
        elseif d==3
                cd \mgqt\non_dec
                filesn
        end

    for k=1:length(flist(:,1))
        file_name=[flist(k,:)];
        flength=length(file_name);
        question=['ZZ',num2str(file_name(3:flength-1)),'4'];
% creates the name of the file that holds the questions(zz*.014) .
```

```
        eval(['load ', file_name]);            % load the data & the file with the
        eval(['load ', question]);             % question number
        file_name=file_name(1:flength-4);      %eleminates the extention(.013)
        question=question(1:flength-4) ;       % in order to use the data.
        Q=eval(question);
        l_rel=max(find(Q(2,:)~=0));            %The length of relevant questions
        l_con=max(find(Q(4,:)~=0));            %The length of control questions
        l_irr=max(find(Q(3,:)~=0));            %The length of irrelevant questions
        qover =l_con+l_rel+l_irr-10;           % finds the number of questions over 10
        offset=qover*(qover>0);
        CRlength=l_rel*6;
        size_M=(10+(qover<0)*qover)*(lf+18)+CRlength;  %total size of features

        initial=zeros(10*(18+lf)+30,1);        %Initializing M with a 10*lf zeros
        M(:,k)=initial;
        M(1:size_M,k)=feature(eval(file_name),[Q(2,:)],[Q(3,:)],[Q(4,:)],feature_list,offset,C
        R_feature);

        eval(['clear ',upper(file_name)])
        eval(['clear ',upper(question)])

    end

        save new_feat M lf flist
        clear M
end
```

```
clear
featlength=23;
load new_feat
for k=1:length(flist(:,1))
        file_name=[flist(k,:)];
        flength=length(file_name);
        question=['ZZ',num2str(file_name(3:flength-1)),'4'];
        eval(['load ',question]);                % load the file with the question numbers.
        Q=eval(question(1:flength-4));           % in order to use the data.
        l_rel=max(find(Q(2,:)~=0));              %The length of relevant questions
        l_con=max(find(Q(4,:)~=0));              %The length of control questions
        l_irr=max(find(Q(3,:)~=0));              %The length of irrelevant questions


% Averaging relevant questions
        for j=1:lf-5+featlength
                m=(j-1)*7;
                clear r
                for i=1:l_rel
                    r(i)=M((i-1)*(lf-5+featlength)+j,k);   %finds the feature values
                end                                        %for all the relevant questions.

                feat_vec(m+1,k)=mean(r);                   %returns mean value for relevant
                feat_vec(m+2,k)=mean(r);
                feat_vec(m+3,k)=max(r);
                feat_vec(m+4,k)=min(r);
                feat_vec(m+5,k)=max(r);
                feat_vec(m+6,k)=min(r);
                feat_vec(m+7,k)=max(r);
        end
  qover =l_con+l_rel+l_irr-10 ;                            %The number of questions over 10
  offset=qover*(qover>0);
  l=(l_irr-offset+l_rel)*(lf-5+featlength);                %The position of the
  cr_l=l+l_con*(lf-5+featlength);                          %first control question

%--------------------------------------

% Averaging control questions

  for j=1:lf-5+featlength
        clear c
        m=(j-1)*7;
        for i=1:l_con
                c(i)=M((i-1)*(lf-5+featlength)+j+l,k);     %finds the feature values for
```

```
        end                                             %all the control questions.

%feature values for control questions

        f(m+1,k)=feat_vec(m+1,k)-mean(c);
                if (feat_vec(m+2,k)+mean(c)==0)
                        f(m+2,k)=100;
                else
                        f(m+2,k)=2*(feat_vec(m+2,k)-
                        mean(c))/(feat_vec(m+2,k)+mean(c));   %for every feature.
                end
        f(m+3,k)=feat_vec(m+3,k)-max(c);
        f(m+4,k)=feat_vec(m+4,k)-min(c);
        f(m+5,k)=feat_vec(m+5,k)-min(c);
        f(m+6,k)=feat_vec(m+6,k)-max(c);
                if max(c)==0
                        f(m+7,k)=100;
                else
                        f(m+7,k)=feat_vec(m+7,k)/max(c);
                end
        end

%---------------------------------------------------
% feature values for control_relevant

  for j=1:6
        m=(j-1)*3;
        clear cr
        for i=1:l_rel
                cr(i)=M((i-1)*6+j+cr_l,k);
        end

        f(m+1+(lf-5+featlength)*7,k)=mean(cr);
        f(m+2+(lf-5+featlength)*7,k)=max(cr);
        f(m+3+(lf-5+featlength)*7,k)=min(cr);
  end

decep(1,k)=Q(1:1);                      % finds if file is deceptive or not
                                        % creates 1 if deceptive and 0 if not.
eval(['clear ',upper(question(1:flength-4))]);
end


save fn_dec f decep
```

Appendix C: Pattern Recognition of the Polygraph Using Fuzzy Set Theory

Shahab Layeghi

Fall 1993

Pattern Recognition of the Polygraph Using Fuzzy Set Theory

A Report
Presented to
The Faculty of the Department of Electrical Engineering
San Jose State University

In Partial Fulfillment
of the Requirements for the Degree
Master of Science

By
Shahab Layeghi

December 1993

Contents:

I. Introduction

Polygraph examinations are the most widely used method to distinguish between truth and deception. In a Polygraph examination a person is connected to a special instrument called a Polygraph which records several physiological signals such as blood pressure, Galvanic Skin Response, and respiration. The subject is asked a set of questions by an examiner. By looking at these signals the examiner is able to determine the reactions of the subject to the questions and decide whether the person was truthful or deceptive in answering each question. The problem with human classification of Polygraph tests is that the outcome depends on the examiner's experience and personal opinion. Automatic scoring of Polygraph tests has been a subject of extensive research. Several methods for Polygraph classification have been studied which are mostly based on statistical classification techniques.

In this study two main goals were presented. The first goal was finding appropriate features which have physiological basis. The second purpose was trying a new classification method based on fuzzy set theory. The advantage of using fuzzy logic is that the it does not simply assigns each input to one of the classes, but it gives the possibility of belonging of an input to each class.

Digitized Polygraph data used in this project were collected from various police stations. The data files were organized according to the test format used and were decoded to ASCII format so they can be read by Matlab. Preprocessing and feature extraction routines were implemented in the Matlab language. Three sets of files were chosen, each one of them contained 50 deceptive and 50 non-deceptive files. These files are listed in Table 10 in Appendix A. A set of features were selected based on physiological reactions, and the feature vectors for every file in each set were found. Different classification methods were studied and a Fuzzy K-nearest neighbor classifier was selected. Significance of each feature was examined according to the clustering and correct classification obtained by using that individual feature. Thirty features were selected as the final set of features and a subset of combinations of 2 to 4 of these features were examined to study the effects of combining the features on classification results. The combination that produced the best classification for all three sets on the average was selected and the effects of changing the classifier parameters on classification was studied.

II. Polygraphs*

A polygraph examination is the most popular method used to determine if an individual is being truthful or deceptive. During an examination, a subject is asked a series of questions and the physiological responses to the questions are recorded using a polygraph. The three physical responses currently obtained from a polygraph examinations are blood pressure, respiration, and skin conductivity. Polygraph charts are usually analyzed by a human interpreter for evidence of truth or deception; however, computer algorithms are now being used to verify results [1][2].

II.1. History

The first attempt to use a scientific instrument in an effort to detect deception occurred around 1895 [3]. That was the year that Caesar Lombroso published the results of his experiments in which a hydrosphygmograph was used to measure the blood pressure-pulse changes of criminals in order to determine whether or not they were deceptive. Although the hydrosphygmograph was originally intended to be used for medical purposes, Lombroso found that it worked well for lie detection. Lombroso may have been the first to use a peak of tension test format. This was done by showing a suspect a series of photographs of children, one being the victim of sexual assault. If the suspect did not react more to the victims picture than the pictures of the other children, Lombroso concluded that the suspect did not know what the victim looked like and therefore was not the alleged perpetrator.

In 1914 Vittorio Benussi published his research on predicting deception by measuring recorded respiration tracings [4]. He found that if the length of inspiration were divide by the length of expiration, the ratio would be larger after lying than before lying and also before telling the truth than after telling the truth. In 1921 John A. Larson constructed an instrument capable of simultaneously recording blood pressure pulse and respiration during an examination [3][4]. Larson reported accurate results which prompted Leonarde Keeler to construct a better version of this instrument in 1926 [3][4].

* This section is exerpted from [17]

The use of galvanic skin response in lie detection began during the turn of the century. It's usefulness, however, did not become evident until the 1930's during which time several articles written by Father Walter G. Summers of Fordham University in New York [4]. In these articles he reports over 90 criminal cases in which examination using the galvanic skin response had all been successful and confirmed by confession or supplementary evidence. The usefulness of the galvanic skin response prompted Keeler to add an galvanometer to his polygraph. At the time of Keelers death in 1949, the Keeler Polygraph recorded blood pressure-pulse, respiration, and galvanic skin response [3].

II.2 Modern Test Formats

The effectiveness of a polygraph examination is often the result of the test format that is used. A polygraph test format consists of an ordered combination of relevant questions about an issue, control questions that provide a physical response for comparison, and irrelevant questions that also provide a response or the lack of a response for comparison [1][4]. Three general types of test formats are in use today. These are Control Question Tests, Relevant-Irrelevant Tests, and Concealed Knowledge Tests. Each of the general test formats may have a number of more specific variations. Each test consists of two to five charts containing a prescribed series of questions. The test format that is used in an examination is determined by the test objective [3][4].

The concealed knowledge test, also called peak of tension test, is used when facts about a crime are known only by the investigators and not by the public. In this case, a subject would not know the facts unless he or she was guilty of the crime. For example, if a gun was used in a crime and the public did not know the caliber, an examiner could ask a suspect if it was a 22 caliber , a 38 caliber, or a 9 mm. If the gun used was a 9 mm and the suspect was deceptive, a polygraph chart would probably indicate evidence of deception.

A control question test is often used in criminal investigations. In this type of test a series of relevant, irrelevant, and control questions are asked. A relevant question is one which is specific to the crime being investigated. For example, " Did you steal the money?". A control question is designed to make the subject feel uncomfortable. It is not specific to the crime being investigated however it may be related in an indirect way. A control question that could follow the relevant question stated above is "Have you ever taken anything that did not belong to you?". The control questions are compared to the relevant questions and if the responses to the relevant questions are greater, the subject is usually classified as deceptive. Irrelevant questions are used as buffers. Examples of irrelevant questions are "Are the lights in this room on?" or "Is today Monday?".

Relevant-Irrelevant tests are usually used to test people trying to obtain security clearance or get a job. In this test, relevant questions are compared to irrelevant questions. Very few control questions are asked. The purpose of control questions in this test is to make sure that the subject is capable of reacting at all.

II.3 Present Day Equipment

The most popular polygraph machines today are the Reid Polygraph developed in 1945 and the Axciton Systems computerized polygraph developed in 1989 [1][11]. The Reid polygraph scrolls a piece of paper under pens that record the biological signals. The Axciton polygraph digitizes physiological signals and uses a computer to process them. The sampling frequency of the Axciton machine is 30 Hz. Axciton provides a computer based system for ranking the subject responses but allows printouts of the charts to be scored by hand the traditional way. Both machines record the same biological signals using standard methods. Blood pressure is measured by placing a standard blood pressure cuff on the arm over the brachial artery. Respiration is monitored by placing rubber tubes around the abdominal area and the chest of the subject. This results in two signals, an upper and lower respiratory signal. Skin conductivity is measured by placing electrodes on two fingers of the same hand.

III. Feature Extraction and Classification

III.1 Introduction

The problem of Classification of Polygraph data like other pattern recognition problems can be considered of consisting of several main stages. Figure [1] shows these stages and the relationship between them. At the beginning data is preprocessed so that noise and redundancies are removed from data and feature extraction can be done more accurately. The next stage is feature extraction. In this step data is read and appropriate features are extracted from it. This is a very important step in all pattern recognition problems, because the purpose of pattern recognition is finding similarities in data that belong to the same class, and features are elements that represent these similarities. Therefore, a good set of features can lead to good classification whereas a satisfactory result cannot be achieved with an inappropriate set of features. Having a set of features, the next step is to use a method to classify data using these features. These steps as applied to Polygraph classification are described in more details in the following sections.

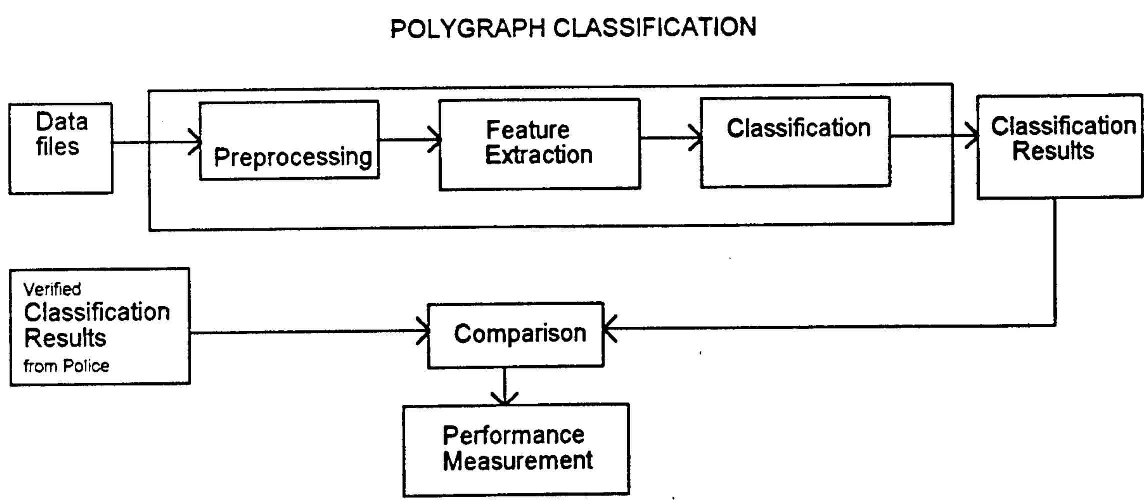

Figure 1

III.2. Preprocessing

Polygraph data consists of signals from four different channels: galvanic skin response (GSR), blood pressure, higher respiration, and lower respiration. First blood pressure signal was decomposed into a high frequency component showing heart pulse, and a low frequency component showing blood volume. Derivative of the blood volume channel was taken and used as another channel. These six derived signals were detrended and filtered. For more details on preprocessing refer to [17].

III.3. Feature Extraction

In this step appropriate features are selected and extracted. Feature extraction is itself divided into several steps. Figure [2] shows different stages involved in feature extraction.

By feature gathering we mean selecting features that might have useful information in them. Feature Combination is a special step in polygraph classification. In this step features derived for different questions in a test are combined to build a single feature. feature selection is a step in which a small number of features is selected from the main feature set to be used in final classifier section.

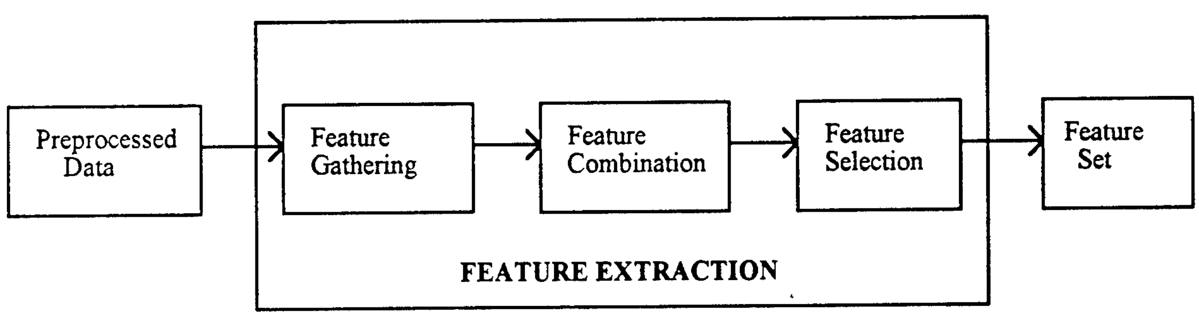

Figure 2

III.3.1. Feature Gathering

Features that possibly convey some information in them were selected and extracted in this stage. Literature about Polygraph were studied and several Polygraph examiners were interviewed to find out what had been done about this problem and what characteristics in a signal are used as indicators of truth or deception. In general features are divided into three main groups, time domain features, frequency domain features and correlation features. Time domain features are mostly standard characteristics like mean, standard deviation, median and so on. Some more specific time domain features were also added, such as the ratio between inhalation and exhalation. Auto Regressive parameters were also extracted and tried as features. To extract each feature for each question a time frame was considered that started with a specific delay after each question was asked and lasted for a specific amount of time. Different time frames were used for different channels because each channel represents a different physiological parameter. Frequency domain features include fundamental frequency, magnitude of power spectral density at fundamental frequency, coherency at fundamental frequency and so on. Figure 3 shows the feature gathering and the decisions that involved in this step.

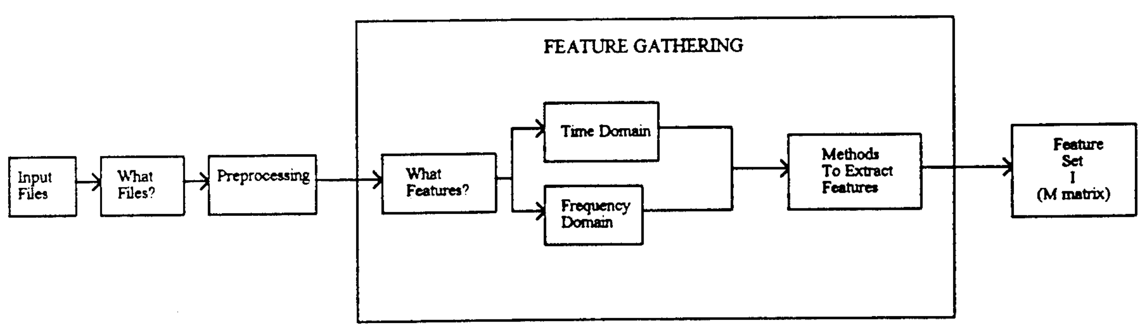

Figure. 3

For every question in a test 93 features were selected and extracted . Also 6 Integrated Spectral Density features were used which directly compare each relevant question to the nearest control question. The total number of features derived for each test was :

$$93\times10+6\times5=960$$

This was repeated for all the tests in feature sets 1, 2 and 3. The results of each set were saved in a 960x100 matrix called the M matrix.

For a detailed description of time domain features and frequency domain features refer respectively to [17] and [16].

III.3.2. Feature Combination

As mentioned earlier each feature is extracted for all questions in a test, that is for relevant, irrelevant, and control questions. In a polygraph test responses to relevant questions are compared to responses to irrelevant and control questions. But in any test there are several questions of each type and many methods can be used to combine them. Figure [4] shows different methods to combine the features. It was decided not to use irrelevant questions in this study, because in a Controlled Question Polygraph Test comparison between the responses to relevant and control questions is the most important factor. For most of the features seven methods were tried to combine features of different questions in a test. For the last six features three ways to combine them were tried. These methods were finding the average, maximum and minimum of relevant-control pairs. The first 93 features combined in seven ways and six integrated spectral density features were combined in three ways so the total number of features at this stage was equal to:

$$(93\times7)+(6\times3)=669$$

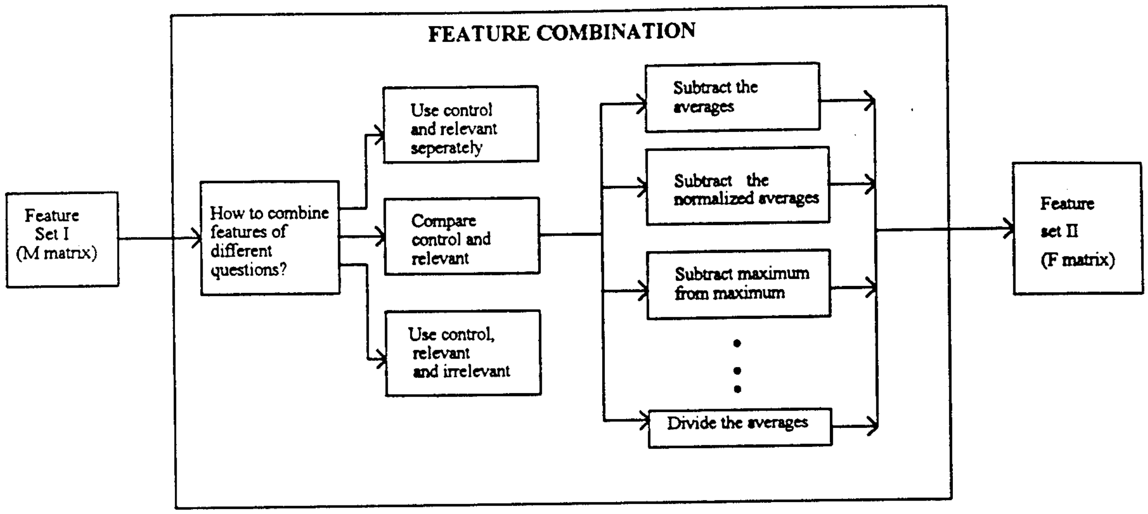

Figure 4

III.3.3 Feature Selection

Feature selection was done in two independent steps, reduction and combination. Figure [5] shows the relationship of these two steps. These two steps are explained in the following two sections.

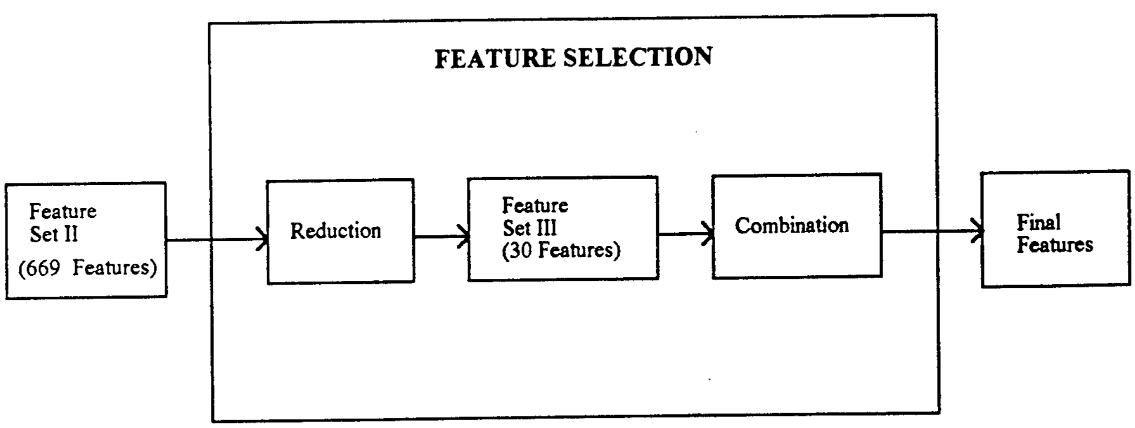

Figure. 5

III.3.3.1 Feature Selection (Reduction)

The next step in our Feature Extraction was to reduce the number of features to a number so that a practical algorithm can be used to select the feature set from them. It was decided to bring down the number of features from 669 to 30 at this step. Two different methods were chosen to test the features one at time to find the best 30. The first method was using the KNN classifier to classify the data files using one feature at a time. It was decided to use a Fuzzy version of K-nearest neighbor algorithm. The value 5 was selected for the K because it seemed that it gave better results than the other values for 1 feature classification . Also a threshold of 0.5 was used to defuzzify the output of the classifier. Refer to the section on classification for the reason of choosing this classifier. The second method was using the scatter criterion is given below.

$$J = \frac{(m_1 - m_2)^2}{s_1^2 + s_2^2} \qquad (1)$$

m_i = mean of class i, s_i = standard deviation of class i

This criterion measures the distance between the means of the two classes, normalized over the sum of the variances. Therefore the more compactly the samples in each class re separated, the higher will be the value of J.

The two methods were run on three sets of data. At this point a method was needed to choose the features. Different methods are possible for this step. The method that was followed is shown in figure [6] and explained below.

At first the results of KNN and scatter criterions were averaged for 3 sets of data so that features that work well for all data sets would be selected. As mentioned in an earlier section for Basic features 1 to 93, 7 features and for the features 94 to 99, 3 features were derived. Because these features are derived from one basic feature and are strongly correlated, it was decided to choose only one from them. So the best feature from these sets of 3 or 7 was selected, and the results were sorted.

Two sets of 30 features were found using the above mentioned criterions. The next step was choosing 30 features from these 60. This was done by examining the tables and selecting the features that showed a good performance in both cases or had a special physical meaning.

This set of features is the final set used for examining and selection. Table 1 in Appendix A shows these features with their corresponding meaning, channel used to derive the feature, and the method to combine the features for different questions.

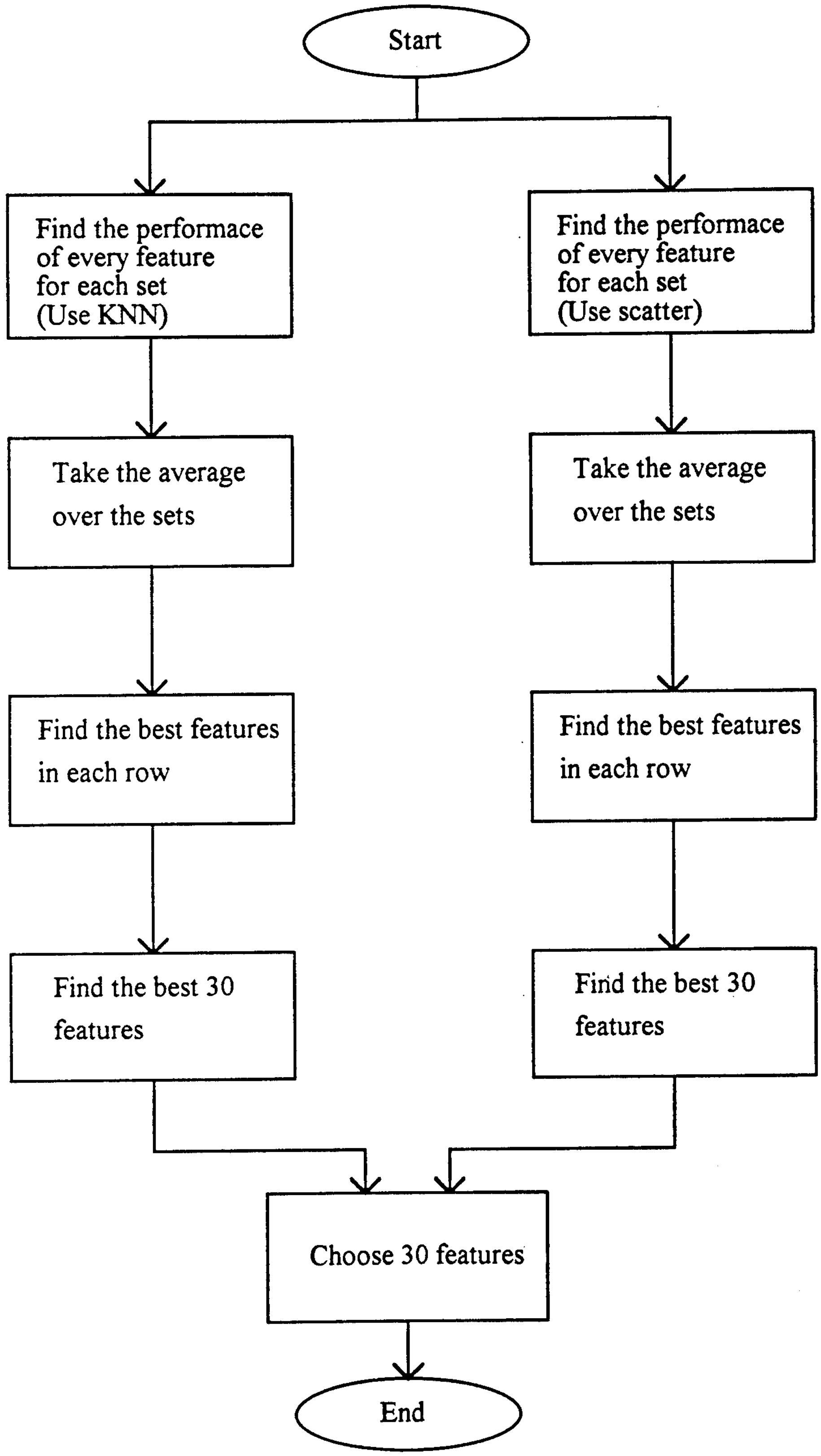

Figure. 6 Feature Selection (Reduction)

III.3.3.2 Feature Selection (Combination)

The number of features was reduced to 30 in the Feature Reduction step. This number should be further reduced because there is 100 samples in each data file, and using 30 features in a classifier might give very good results for that particular data set, but it won't be able to generalize. At this step measuring the performance of individual features is not a very logical method. Because for example features 'A' and "B' might be good features individually, but combining them might not necessarily give better results. Whereas feature 'C' that might not be a very good feature by itself might improve the classification if combined with feature 'A'.

Therefore the combinations of the features should be examined. Many methods are suggested to solve this problem. The most basic way is exhaustive search. That is trying all the combinations for these features. It is obvious that this is not practical when the number of features is not very small. For example choosing 10 or less features from a set of 30 and trying all the different combinations needs

$$\sum_{i=1}^{10} \binom{i}{30} = \sum_{i=1}^{10} \frac{30!}{i!(30-i)!} \approx 10^8$$

computations.

The method that was chosen was to start with all the combinations of two, find the best N ones among them, and use only these combinations to combine features in sets of 3. Then again find the best combinations of 3 and use them in combinations of 4 features.

This procedure is continued until satisfactory results are gained or features are not improved by increasing the number of features. Figure [7] shows the algorithm for this step.

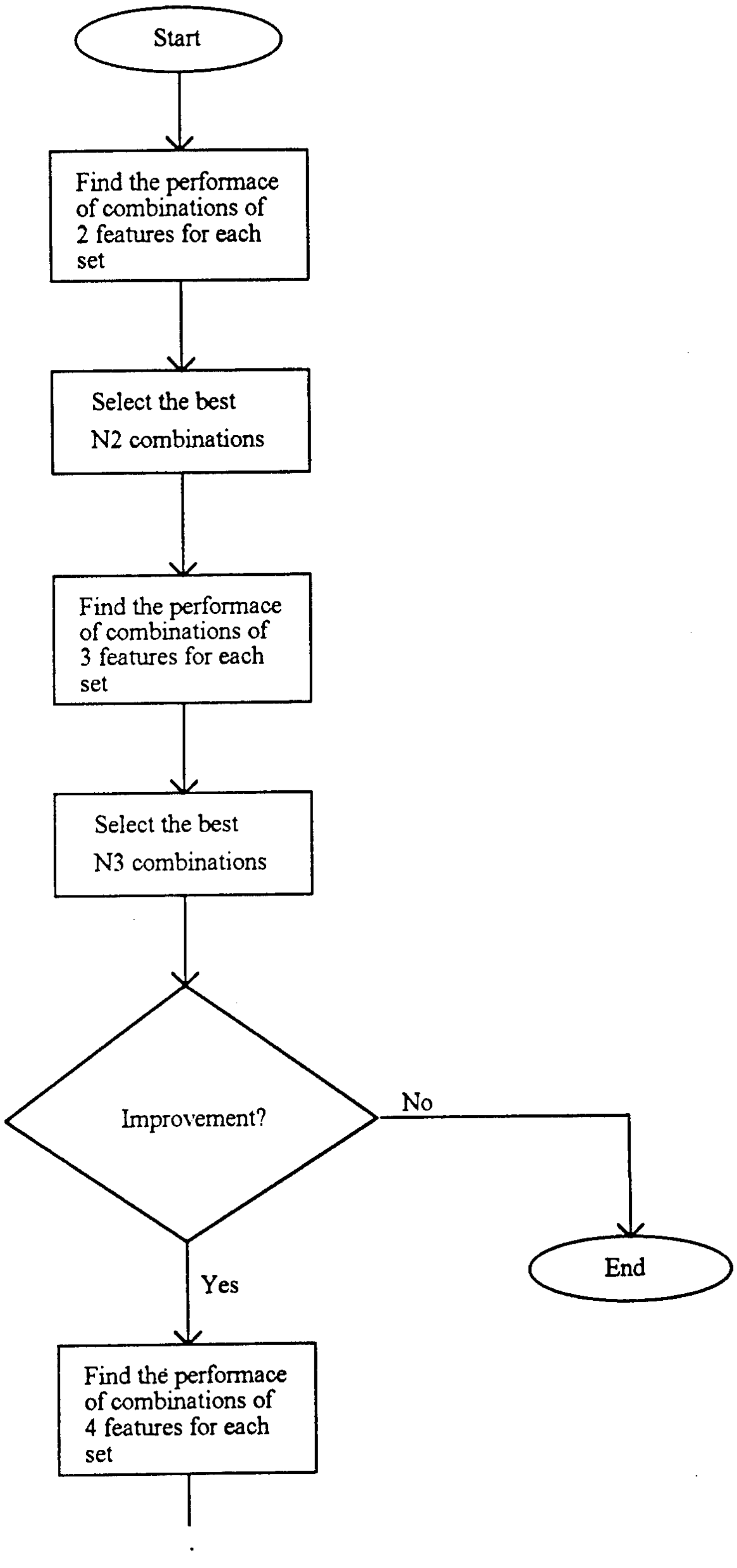

Figure 7. Feature Selection (Combination)

All pairwise combinations of the features were tried to see the classification results. The classifier used was Fuzzy K-nearest neighbor with a threshold of 0.5, and K=5. This was done for three sets of features. The results were sorted and 30 best combinations for each set were found. Also the results of classification for each combination for the 3 sets was averaged and the 30 combinations that gave best results on the average were found. These combinations are shown in Table 2 in Appendix A.

It was decided to select 20 sets of pairwise combinations to use in combinations of 3. Results for sets 1-3 and Average were studied and combinations that showed a good result in one of the sets or had a good average were selected. Table 3 in Appendix A shows these combinations.

The same steps were repeated to study the combinations of 3 and 4 features. The results are shown in Tables 4 and 6 in Appendix A. Because of time limitations it was decided not to go further from combinations of 4 features.

III.3.4 Discussion about the results:

The classification results improved consistently by increasing the number of features from one to four. The features that showed the best result for the three sets were features {5, 9, 21, 23}with 81 percent correct classification. These features represent Maximum Of GSR, Difference between Maximum and Minimum of High Cardio, Maximum of Lower Respiratory, and the Difference between Maximum and Minimum of Upper Respiratory. These features show approximately the same classification results for all three sets which is 81 percent.

Other combinations of features also gave comparable results. For example {5, 21, 23, 29} and {5, 11, 21, 23}, and {5, 10, 21, 23}. Note the repetition of {5, 21, 23}. Refer to the table 1 in Appendix A for a meaningful listing of the features. It is very notable that feature sets that show the best classification results has features that come from different channels. It can be concluded that signals from different physiological channels convey independent information, so that using features extracted from them improves the classification.

Another point to notice is that data set three shows better classification results than the two other sets, 87 percent versus 81 percent for the sets one and two. The feature set that gives the best result for data set three is {9, 14, 19, 24}. This feature set gives 87.4 percent correct classification for data set three. The feature set {5, 9, 21, 23} that gives the best classification on the average, has approximately the same results for all three sets, 81 percent. The polygraph tests that were used in this project came from several sources and were done by different examiners that used slightly different methods. Fifty consecutive tests were used to build each data set. So it is possible that some characteristic exists in the deceptive files of data set three that results in better classification. This is a matter of future investigation.

III.4. Classification

The classifier is the final stage in a pattern recognition system. The inputs to the classifier are usually a set of feature vectors. The classifier ordinarily assigns each input to one of the classes. There are many methods to design a classifier. The classifier could be designed after studying the distribution of samples of each class, or a learning classification algorithm can be implemented. We were not sure about the shape of clustering and the distribution of samples for deceptive and non deceptive classes, and it was possible that samples for one class cluster around more than one point in space. It was decided to use the K-nearest neighbor classifier* in this project because it does not explicitly use the distribution of the samples.

One of the characteristics of the conventional classification methods is that they assign each input to one of the possible classes (crisp Classification) or find probability distributions of belongingnesses of the inputs to the classes. While the way that humans think and classify objects is fundamentally different. Each object can be considered to belong to more than one class at the same time, and there are degrees of belongingness for each class. This is the basic idea that is followed in Fuzzy Logic. It was decided to follow a Fuzzy Logic based classifier in this project, because the output will be the possibility of deception and a person will not be considered completely deceptive or non deceptive.

Conventional K-nearest neighbor algorithm and a Fuzzy version of it are described in the following two sections.

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* We are indebted to Professor R. Duda for suggesting KNN classifier.

III.4.1. K-Nearest Neighbor Algorithm

K-Nearest neighbor algorithm is a supervised classification method. There is no need for the training or adjusting the classifier. A set of labeled input samples is given to the classifier. When a new sample is given to the system, it finds its K nearest neighboring samples, and assigns this sample to the class that the majority of the neighbors belong to. K could be any positive integer. When K is set to 1, the algorithm is called the nearest neighbor algorithm. In this case each new sample is assigned to the class of its nearest neighbor. If K is greater than 1, it is possible that there is no majority class. To remove this tie, the sum of the distances of the new sample to its neighbors in each class is computed and the sample is assigned to the class that has the minimum distance. The main advantage of using this method is that the samples of each class are not needed to cluster in a pre specified shape. For example for a two class classification, the K-nearest neighbor classifier can still give very good results if the samples of each class are clustered in two distinct points in the space. The algorithm for the K nearest neighbor is shown in figure 8. It is supposed that C is the number of classes, K is the number of neighbors in KNN, $x_i x_i$ is the *ith* labeled sample and y is the input to be classified.

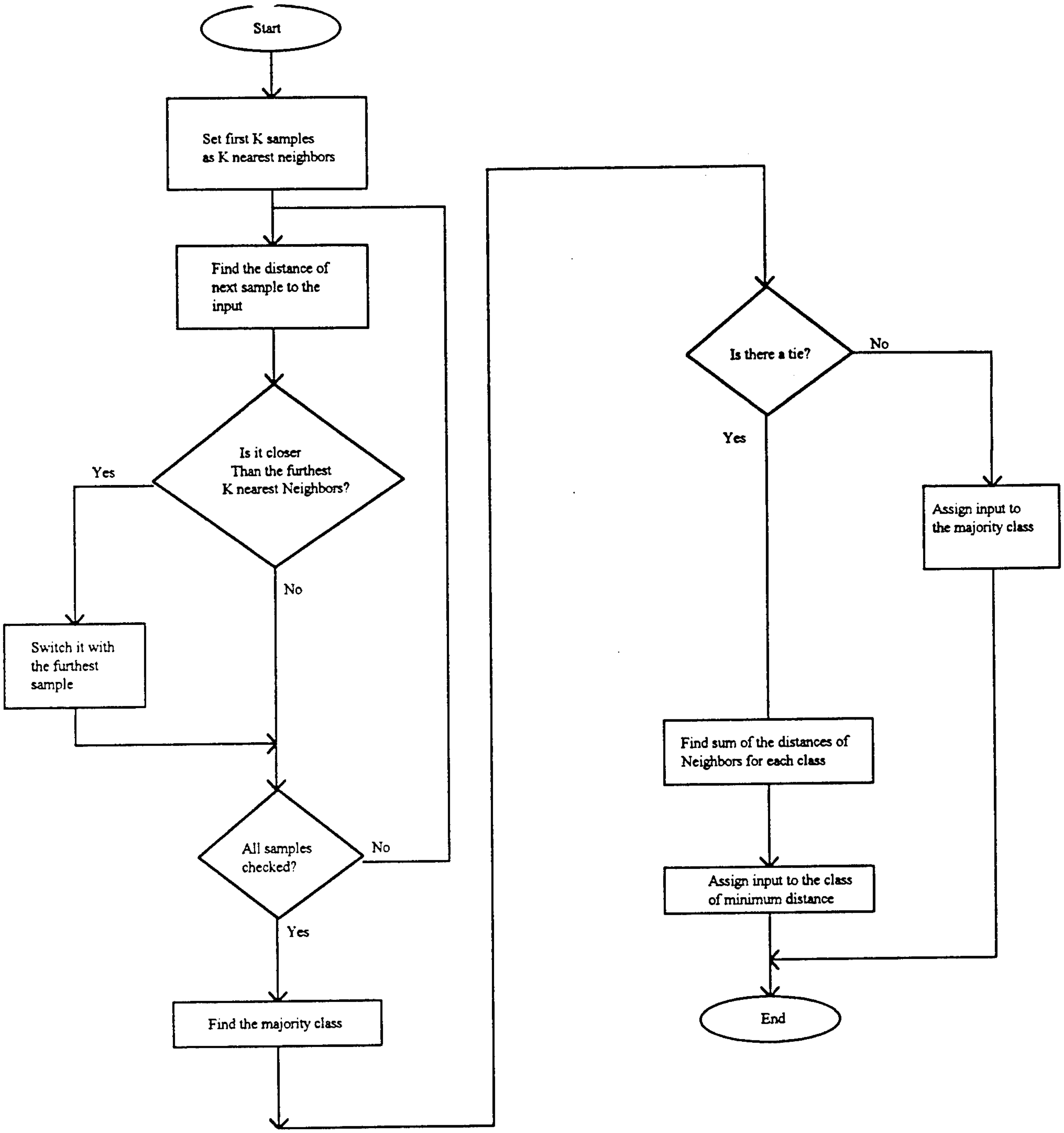


Figure 8. K Nearest Neighbor Algorithm

III.4.2. Fuzzy K Nearest Neighbor Algorithm

The fuzzy K nearest neighbor algorithm uses the same idea of conventional K nearest neighbor algorithm, that is finding the K samples that are closest to sample to be classified. But there is a conceptual difference in classification. When fuzzy classification is used, the input is not assigned to a single class. Instead, the degree of belongingness of the input to each class is determined by the classifier. By using this method more information is obtained about the input. For example if the result of classification determines membership of an input to class A is 0.9 and to class B is 0.1, it means the input belongs to class A with a very good possibility. But if the membership to class A is 0.55 and to class B is 0.45, it means that we cannot be very sure about the classification of the input. If the crisp classifier is used, in both cases the input will be assigned to class A and no further information is obtained.

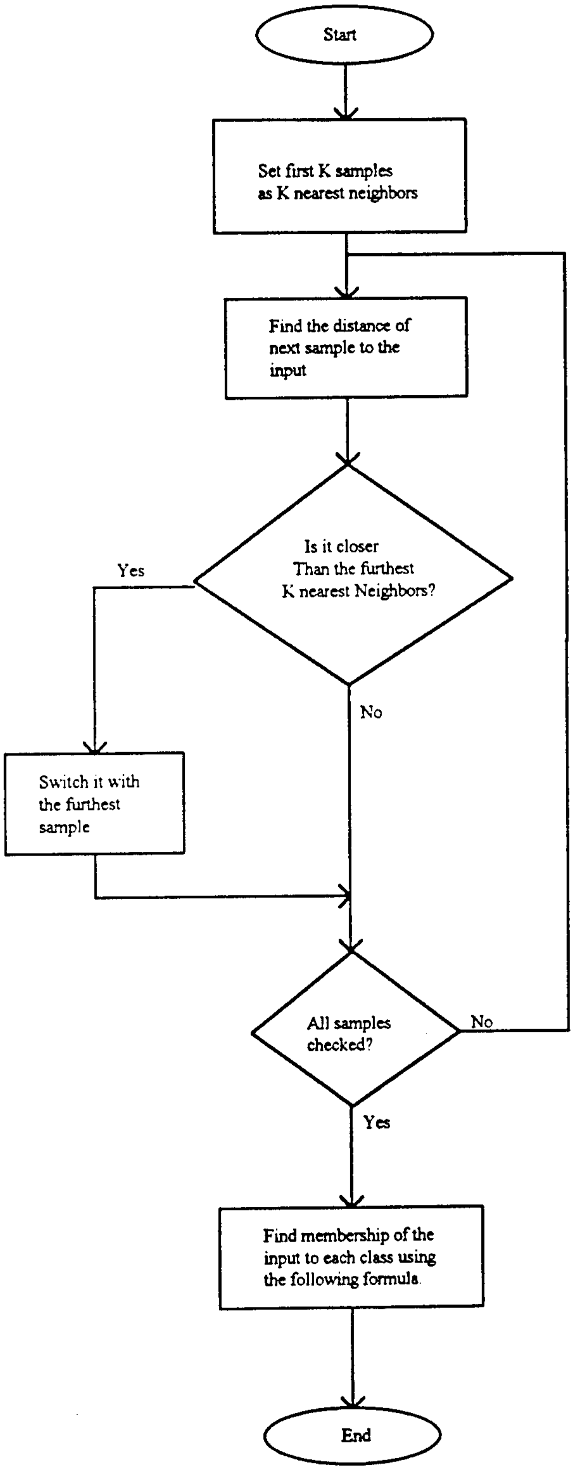
Refer to [14, 15] for more detailed discussions about fuzzy K nearest neighbor algorithms. The flowchart for a fuzzy K nearest neighbor classifier is drawn in figure 9.

The first step in the fuzzy K nearest neighbor algorithm is the same as first step in crisp classifier. In both cases K nearest neighbors of the input are found. While in crisp classifier the majority class of the neighbors is assigned to the input, in Fuzzy classifier membership of the input to each class should be found. In order to do so the membership vector of each sample is combined to obtain the membership vector of the input. If the samples are crisply classified, membership vectors should be assigned to them. One method to do so is to assign the membership of 1 to the class that it belongs to, and membership of 0 to other classes. Other methods assign different memberships to the samples according to its distance from the mean of the class, or the distances from the nearby samples of its own class and the other classes.

When the membership vectors of the labeled samples are specified, they are combined to find the membership vector of the unknown class. This procedure should be done in a way that samples that are closer to the input have more effect on the resultant membership function. The following formula uses the inverse distance to weigh the membership functions. x is the input to be classified, x_j is the jth nearest neighbor and u_{ij} is the membership of the jth nearest neighbor of the input in class i. D(x,y) is a distance measure between the vectors x and y which could be the Euclidean distance.

$$u_i(x) = \frac{\sum_{j=1}^{K} u_{ij}(1/D(x,x_j)^{\frac{1}{m-1}})}{\sum_{j=1}^{K}(1/D(x,x_j)^{\frac{1}{m-1}})}$$

m is a parameter that changes the weighing effect of the distance. When $m >> 1$, all the samples will have the same weight. When m approaches 1, the nearest samples have much more effect on the membership value of the input.



$$u_i(x) = \frac{\sum_{j=1}^{K} u_{ij} (1 / D(x, x_j)^{\frac{1}{m-1}})}{\sum_{j=1}^{K} (1 / D(x, x_j)^{\frac{1}{m-1}})}$$

Figure 9. Fuzzy K-Nearest Neighbor Algorithm

III.4.3. Methods and Discussion:

As mentioned in an earlier section the classifier was needed to compare the effectiveness of single features and to choose the combinations of the features that gave the best classification results. Therefore, the classifier was selected and used before the final feature set was determined. The classifier might change the results of the classification and finding the best classifier is not a trivial task. For example using the value of 10 for K may change the set of 30 best features that was found by using K = 5.

It is not practical to try all different cases for different classifiers and different parameters of classifiers, so it was decided to use a classifier with fixed parameters up to the point that final set of features were selected. The classifier as mentioned earlier was a Fuzzy K-nearest neighbor with the following parameters:

K = 5,

m = 2,

Defuzzification threshold = 0.5;

It should be noted that in order to save computation time throughout this project, each set of files was randomly broken into a training and a testing set. Each file in the testing set was classified using the labeled files in training set. Each experiment was repeated 20 times, and the results were averaged. The number of files that were used for training and testing were accordingly 75 and 25. In the last stage of experiments after the final feature set had been fixed, instead of randomly selecting testing and training files, one file was kept for testing each time and the experiment was repeated 100 times changing the test file.

After the final feature set was selected (Refer to the section on Feature Extraction), different values for K were tried on fuzzy and crisp classifier to compare the two classifiers and find the best parameters. In addition to percentage of correct classification a measure of performance was also used which is explained below.

The measure that is used to compare the performance of fuzzy classifier is the root mean square of the distances between the output of the classifier and the correct class. The correct ouput of the classifer should be 0 for non-deceptive cases and 1 for the deceptive ones. For example if for a deceptive sample the classifier output is 0.8, 0.2 is the distance between the output and the correct class. The same measure is used for the crisp classifier. In the case of the crisp classifier the distance is always 0 for correct classification and 1 for incorrect classification.

For the fuzzy classifier the threshold used for defuzzification was also changed to find the optimum value. Tables 7 and 8 in Appendix A show the results. The best classification on the average over three sets is obtained using the fuzzy classifier with K = 6, and threshold = 0.6 . Using this values correct classification of 81.6 percent was achieved. The best result using the crisp classifier was 80.6 percent which was obtained using K=6. The performance measures for the fuzzy and crisp classifiers were accordingly 0.3915 and 0.4377 which shows fuzzy classifier has a better performance in this respect.

One final experiment that was done is explained below. In a Polygraph examination a set of questions is repeated one to five times and the decision is made by considering the responses to all these charts. In this project each chart was classified separately. As the final experiment responses to all the charts in a Polygraph examination were combined and classified as deceptive or non-deceptive. The way they were combined was finding the majority class and assigning the case to that class. In the case that equal number of files classified as deceptive and non-deceptive, the membership function of the files was averaged and the case was classified according to this value. The classification results for all the files in sets 1 to 3 are shown in Table 9 in Appendix A. The number of cases in each set was 35. The number of misclassified cases in sets 1 to 3 are 5, 7, and 3, which correspond to correct classifications of 85.7, 80.0, and 91.4 percent.

IV. Conclusion and future work

The set of four features that showed best classification results in this project were Maximum of GSR, Upper Respiration and Lower respiration signals, and the difference between the Maximum and Minimum of High Cardio signal. These are all very simple time domain features. The best classification was obtained using the fuzzy classifier with K = 6, and threshold = 0.6 . Using this values correct classification of 81.6 percent was achieved. By combining all the files in a Polygraph examination 85.7 percent correct classification was achieved on the average.

There are several suggestions for the future work. First is to repeat this work with larger sets of data files and observe the generalizability of the feature sets obtained in this research. A possible way to improve the results is to change time frames used to extract each feature for every question. In this way the optimum time for obtaining a response could be found. Another suggestion is to try different methods for fuzzification and defuzzification of feature vectors to optimize the fuzzy classifier.

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Appendices

Appendix A:
Tables

No.	feature	Description	Channel	Method
1	10mean	mean	GSR	1
2	10curve	curve length	GSR	2
3	10med_dif	median of the derivative	GSR	1
4	10max_min	minimum subtracted from the maximum	GSR	2
5	10max	maximum of the signal	GSR	1
6	10mdif	mean of derivative	GSR	3
7	20curve	curve length	High Cardio	1
8	20ampcard	amplitude of the peaks	High Cardio	1
9	20max_min	minimum subtracted from the maximum	High Cardio	4
10	20max	maximum of the signal	High Cardio	4
11	20min	minimum of the signal	High Cardio	1
12	30med_dif	median of the derivative	Low Cardio	3
13	30max	maximum of the signal	Low Cardio	1
14	40mean	mean	Derivative of Low Cardio	1
15	40max	maximum of the signal	Derivative of Low Cardio	1
16	50curve	curve length	Lower Respiratory	6
17	50ampr	amplitude of the peaks	Lower Respiratory	2
18	50peaknumr	number of the peaks	Lower Respiratory	5
19	50ie	inhalation divided by exhalation	Lower Respiratory	5
20	50max_min	minimum subtracted from the maximum	Lower Respiratory	2
21	50max	maximum of the signal	Lower Respiratory	6
22	60max_min	minimum subtracted from the maximum	Upper Respiratory	2
23	60max	maximum	Upper Respiratory	3
24	10std	standard deviation	GSR	2
25	20std	standard deviation	High Cardio	1
26	50std	standard deviation	Upper Respiratory	6
27	20armod1	auto regressive parameter	High Cardio	7
28	26psdcoh1	max cross spectral density	High Cardio, Lower Respiratory	1
29	10isd1	frequency of maximum integrated spectral difference of control-relevant pair	GSR	1*
30	20isd1	area under integrated spectral difference	High Cardio	3*

Methods: 1=Difference of Averages, 2=Normalized Average, 3=Max-Max, 4=Min-Min, 5=Max-Min, 6=Min-Max, 7=Max/Min , 1*=Average of relevant-control pairs, 3*=Max of relevant-control pair.

Table 1. Selected Features

Percentage of correct classification for 30 best combinations in set 1

Percent correct	Feature 1	Feature 2
74.2000	8.0000	18.0000
74.0000	10.0000	21.0000
73.0000	5.0000	7.0000
72.0000	24.0000	26.0000
71.8000	23.0000	24.0000
71.6000	4.0000	26.0000
70.4000	25.0000	26.0000
70.4000	18.0000	25.0000
70.2000	24.0000	27.0000
70.2000	9.0000	21.0000
70.0000	5.0000	27.0000
69.6000	11.0000	21.0000
69.6000	9.0000	24.0000
69.4000	11.0000	27.0000
69.4000	5.0000	26.0000
69.2000	8.0000	19.0000
69.2000	5.0000	18.0000
69.0000	25.0000	27.0000
69.0000	9.0000	18.0000
69.0000	5.0000	23.0000
68.8000	24.0000	30.0000
68.8000	18.0000	20.0000
68.8000	17.0000	20.0000
68.8000	4.0000	15.0000
68.6000	22.0000	24.0000
68.4000	6.0000	24.0000
68.4000	1.0000	27.0000
68.2000	15.0000	24.0000
68.2000	9.0000	26.0000
68.2000	5.0000	19.0000

Table [2.1] Results of pairwise combinations of features

Percentage of correct classification for 30 best combinations in set 2

Percent correct	Feature 1	Feature 2
74.4000	5.0000	23.0000
74.4000	4.0000	27.0000
74.2000	4.0000	15.0000
74.0000	20.0000	24.0000
73.6000	16.0000	24.0000
73.2000	3.0000	27.0000
72.8000	27.0000	30.0000
72.6000	4.0000	30.0000
72.6000	4.0000	7.0000
72.4000	5.0000	25.0000
72.2000	24.0000	30.0000
72.2000	8.0000	27.0000
72.2000	4.0000	17.0000
72.2000	4.0000	16.0000
72.0000	24.0000	27.0000
72.0000	24.0000	25.0000
72.0000	4.0000	20.0000
71.8000	7.0000	23.0000
71.8000	4.0000	10.0000
71.2000	25.0000	27.0000
70.8000	24.0000	26.0000
70.8000	8.0000	22.0000
70.6000	7.0000	27.0000
70.6000	6.0000	27.0000
70.4000	14.0000	21.0000
70.4000	14.0000	20.0000
70.4000	4.0000	8.0000
70.2000	4.0000	24.0000
70.0000	22.0000	27.0000
70.0000	17.0000	24.0000

Table [2.2] Results of pairwise combinations of features

Percentage of correct classification for 30 best combinations in set 3

Percent correct	Feature 1	Feature 2
81.0000	1.0000	10.0000
80.6000	9.0000	24.0000
80.4000	10.0000	24.0000
80.4000	4.0000	25.0000
80.2000	4.0000	9.0000
79.8000	5.0000	11.0000
79.2000	17.0000	24.0000
79.2000	1.0000	21.0000
79.2000	1.0000	8.0000
79.0000	1.0000	24.0000
79.0000	1.0000	11.0000
78.8000	4.0000	11.0000
78.6000	4.0000	17.0000
78.2000	24.0000	25.0000
78.2000	1.0000	14.0000
78.0000	1.0000	23.0000
78.0000	1.0000	20.0000
77.8000	23.0000	24.0000
77.8000	1.0000	5.0000
77.6000	19.0000	24.0000
77.4000	11.0000	24.0000
77.4000	5.0000	18.0000
77.2000	4.0000	19.0000
77.0000	4.0000	18.0000
76.8000	4.0000	15.0000
76.6000	5.0000	13.0000
76.6000	4.0000	24.0000
76.2000	4.0000	5.0000
76.2000	1.0000	26.0000

Table [2.3] Results of pairwise combinations of features

Percentage of correct classification for 30 best combinations in average

Percent correct	Feature 1	Feature 2
73.2667	4.0000	15.0000
72.8000	24.0000	26.0000
72.6667	4.0000	17.0000
72.6000	5.0000	23.0000
72.2667	23.0000	24.0000
72.0667	24.0000	30.0000
71.9333	20.0000	24.0000
71.8667	24.0000	27.0000
71.4667	24.0000	25.0000
71.4000	4.0000	26.0000
71.0667	4.0000	10.0000
70.9333	1.0000	8.0000
70.9333	4.0000	23.0000
70.6000	5.0000	11.0000
70.6000	4.0000	24.0000
70.5333	9.0000	24.0000
70.4667	6.0000	24.0000
70.4667	4.0000	25.0000
70.4667	4.0000	19.0000
70.4000	4.0000	30.0000
70.3333	1.0000	23.0000
70.0667	17.0000	24.0000
70.0667	1.0000	24.0000
70.0000	16.0000	24.0000
69.9333	4.0000	9.0000
69.8667	4.0000	20.0000
69.8667	5.0000	7.0000
69.8667	4.0000	7.0000
69.8000	15.0000	24.0000
69.8000	1.0000	21.0000

Table [2.4] Results of pairwise combinations of features

4	15
24	26
4	17
5	3
23	24
24	30
20	24
24	27
24	25
4	26
1	10
9	24
10	24
5	11
17	24
4	27
16	24
8	18
10	21
5	7

Table [3]. 20 combinations of 2 features selected to combine in sets of 3

Percentage of correct classification for 30 best combinations in set 1

Percent correct	Feature 1	Feature 2	Feature 3
79.4000	10.0000	21.0000	26.0000
77.6000	5.0000	7.0000	23.0000
77.6000	5.0000	23.0000	11.0000
77.4000	5.0000	23.0000	21.0000
76.4000	16.0000	24.0000	18.0000
76.4000	5.0000	23.0000	19.0000
75.8000	23.0000	24.0000	19.0000
75.8000	23.0000	24.0000	15.0000
75.8000	5.0000	23.0000	7.0000
75.6000	5.0000	7.0000	22.0000
75.6000	5.0000	7.0000	21.0000
75.6000	5.0000	7.0000	16.0000
75.4000	5.0000	7.0000	14.0000
75.4000	5.0000	11.0000	10.0000
75.2000	10.0000	21.0000	19.0000
75.2000	8.0000	18.0000	6.0000
75.2000	5.0000	23.0000	2.0000
75.0000	10.0000	21.0000	16.0000
75.0000	10.0000	21.0000	8.0000
75.0000	5.0000	11.0000	18.0000
75.0000	4.0000	26.0000	14.0000
75.0000	5.0000	23.0000	29.0000
75.0000	5.0000	23.0000	25.0000
74.8000	10.0000	21.0000	9.0000
74.6000	10.0000	21.0000	12.0000
74.6000	5.0000	11.0000	23.0000
74.6000	10.0000	24.0000	9.0000
74.6000	5.0000	23.0000	10.0000
74.6000	5.0000	23.0000	9.0000
74.4000	5.0000	7.0000	19.0000

Table [4.1] Results of combinations of 3 features

Percentage of correct classification for 30 best combinations in set 2

Percent correct	Feature 1	Feature 2	Feature 3
79.8000	20.0000	24.0000	12.0000
78.6000	24.0000	30.0000	19.0000
78.6000	4.0000	15.0000	28.0000
78.0000	24.0000	27.0000	19.0000
77.8000	4.0000	17.0000	19.0000
77.6000	8.0000	18.0000	4.0000
77.4000	4.0000	27.0000	19.0000
77.4000	5.0000	23.0000	21.0000
77.2000	5.0000	23.0000	29.0000
77.2000	4.0000	15.0000	27.0000
77.0000	4.0000	27.0000	18.0000
77.0000	4.0000	15.0000	21.0000
76.6000	5.0000	7.0000	23.0000
76.6000	20.0000	24.0000	3.0000
76.4000	16.0000	24.0000	30.0000
76.4000	4.0000	27.0000	25.0000
76.4000	24.0000	27.0000	10.0000
76.4000	23.0000	24.0000	30.0000
76.2000	5.0000	23.0000	3.0000
76.2000	4.0000	17.0000	2.0000
76.2000	4.0000	15.0000	26.0000
75.8000	5.0000	7.0000	15.0000
75.8000	24.0000	30.0000	4.0000
75.8000	5.0000	23.0000	28.0000
75.6000	4.0000	27.0000	15.0000
75.6000	24.0000	27.0000	26.0000
75.6000	24.0000	27.0000	1.0000
75.6000	20.0000	24.0000	25.0000
75.6000	24.0000	30.0000	16.0000
75.4000	4.0000	15.0000	8.0000

Table [4.2] Results of combinations of 3 features

Appendices

Appendix A:
Tables

No.	feature	Description	Channel	Method
1	10mean	mean	GSR	1
2	10curve	curve length	GSR	2
3	10med_dif	median of the derivative	GSR	1
4	10max_min	minimum subtracted from the maximum	GSR	2
5	10max	maximum of the signal	GSR	1
6	10mdif	mean of derivative	GSR	3
7	20curve	curve length	High Cardio	1
8	20ampcard	amplitude of the peaks	High Cardio	1
9	20max_min	minimum subtracted from the maximum	High Cardio	4
10	20max	maximum of the signal	High Cardio	4
11	20min	minimum of the signal	High Cardio	1
12	30med_dif	median of the derivative	Low Cardio	3
13	30max	maximum of the signal	Low Cardio	1
14	40mean	mean	Derivative of Low Cardio	1
15	40max	maximum of the signal	Derivative of Low Cardio	1
16	50curve	curve length	Lower Respiratory	6
17	50ampr	amplitude of the peaks	Lower Respiratory	2
18	50peaknumr	number of the peaks	Lower Respiratory	5
19	50ie	inhalation divided by exhalation	Lower Respiratory	5
20	50max_min	minimum subtracted from the maximum	Lower Respiratory	2
21	50max	maximum of the signal	Lower Respiratory	6
22	60max_min	minimum subtracted from the maximum	Upper Respiratory	2
23	60max	maximum	Upper Respiratory	3
24	10std	standard deviation	GSR	2
25	20std	standard deviation	High Cardio	1
26	50std	standard deviation	Upper Respiratory	6
27	20armod1	auto regressive parameter	High Cardio	7
28	26psdcoh1	max cross spectral density	High Cardio, Lower Respiratory	1
29	10isd1	frequency of maximum integrated spectral difference of control-relevant pair	GSR	1*
30	20isd1	area under integrated spectral difference	High Cardio	3*

Methods: 1=Difference of Averages, 2=Normalized Average, 3=Max-Max, 4=Min-Min, 5=Max-Min, 6=Min-Max, 7=Max/Min , 1*=Average of relevant-control pairs, 3*=Max of relevant-control pair.

Table 1. Selected Features

Percentage of correct classification for 30 best combinations in set 1

Percent correct	Feature 1	Feature 2
74.2000	8.0000	18.0000
74.0000	10.0000	21.0000
73.0000	5.0000	7.0000
72.0000	24.0000	26.0000
71.8000	23.0000	24.0000
71.6000	4.0000	26.0000
70.4000	25.0000	26.0000
70.4000	18.0000	25.0000
70.2000	24.0000	27.0000
70.2000	9.0000	21.0000
70.0000	5.0000	27.0000
69.6000	11.0000	21.0000
69.6000	9.0000	24.0000
69.4000	11.0000	27.0000
69.4000	5.0000	26.0000
69.2000	8.0000	19.0000
69.2000	5.0000	18.0000
69.0000	25.0000	27.0000
69.0000	9.0000	18.0000
69.0000	5.0000	23.0000
68.8000	24.0000	30.0000
68.8000	18.0000	20.0000
68.8000	17.0000	20.0000
68.8000	4.0000	15.0000
68.6000	22.0000	24.0000
68.4000	6.0000	24.0000
68.4000	1.0000	27.0000
68.2000	15.0000	24.0000
68.2000	9.0000	26.0000
68.2000	5.0000	19.0000

Table [2.1] Results of pairwise combinations of features

Percentage of correct classification for 30 best combinations in set 2

Percent correct	Feature 1	Feature 2
74.4000	5.0000	23.0000
74.4000	4.0000	27.0000
74.2000	4.0000	15.0000
74.0000	20.0000	24.0000
73.6000	16.0000	24.0000
73.2000	3.0000	27.0000
72.8000	27.0000	30.0000
72.6000	4.0000	30.0000
72.6000	4.0000	7.0000
72.4000	5.0000	25.0000
72.2000	24.0000	30.0000
72.2000	8.0000	27.0000
72.2000	4.0000	17.0000
72.2000	4.0000	16.0000
72.0000	24.0000	27.0000
72.0000	24.0000	25.0000
72.0000	4.0000	20.0000
71.8000	7.0000	23.0000
71.8000	4.0000	10.0000
71.2000	25.0000	27.0000
70.8000	24.0000	26.0000
70.8000	8.0000	22.0000
70.6000	7.0000	27.0000
70.6000	6.0000	27.0000
70.4000	14.0000	21.0000
70.4000	14.0000	20.0000
70.4000	4.0000	8.0000
70.2000	4.0000	24.0000
70.0000	22.0000	27.0000
70.0000	17.0000	24.0000

Table [2.2] Results of pairwise combinations of features

Percentage of correct classification for 30 best combinations in set 3

Percent correct	Feature 1	Feature 2
81.0000	1.0000	10.0000
80.6000	9.0000	24.0000
80.4000	10.0000	24.0000
80.4000	4.0000	25.0000
80.2000	4.0000	9.0000
79.8000	5.0000	11.0000
79.2000	17.0000	24.0000
79.2000	1.0000	21.0000
79.2000	1.0000	8.0000
79.0000	1.0000	24.0000
79.0000	1.0000	11.0000
78.8000	4.0000	11.0000
78.6000	4.0000	17.0000
78.2000	24.0000	25.0000
78.2000	1.0000	14.0000
78.0000	1.0000	23.0000
78.0000	1.0000	20.0000
77.8000	23.0000	24.0000
77.8000	1.0000	5.0000
77.6000	19.0000	24.0000
77.4000	11.0000	24.0000
77.4000	5.0000	18.0000
77.2000	4.0000	19.0000
77.0000	4.0000	18.0000
76.8000	4.0000	15.0000
76.6000	5.0000	13.0000
76.6000	4.0000	24.0000
76.2000	4.0000	5.0000
76.2000	1.0000	26.0000

Table [2.3] Results of pairwise combinations of features

Percentage of correct classification for 30 best combinations in average

Percent correct	Feature 1	Feature 2
73.2667	4.0000	15.0000
72.8000	24.0000	26.0000
72.6667	4.0000	17.0000
72.6000	5.0000	23.0000
72.2667	23.0000	24.0000
72.0667	24.0000	30.0000
71.9333	20.0000	24.0000
71.8667	24.0000	27.0000
71.4667	24.0000	25.0000
71.4000	4.0000	26.0000
71.0667	4.0000	10.0000
70.9333	1.0000	8.0000
70.9333	4.0000	23.0000
70.6000	5.0000	11.0000
70.6000	4.0000	24.0000
70.5333	9.0000	24.0000
70.4667	6.0000	24.0000
70.4667	4.0000	25.0000
70.4667	4.0000	19.0000
70.4000	4.0000	30.0000
70.3333	1.0000	23.0000
70.0667	17.0000	24.0000
70.0667	1.0000	24.0000
70.0000	16.0000	24.0000
69.9333	4.0000	9.0000
69.8667	4.0000	20.0000
69.8667	5.0000	7.0000
69.8667	4.0000	7.0000
69.8000	15.0000	24.0000
69.8000	1.0000	21.0000

Table [2.4] Results of pairwise combinations of features

4	15
24	26
4	17
5	3
23	24
24	30
20	24
24	27
24	25
4	26
1	10
9	24
10	24
5	11
17	24
4	27
16	24
8	18
10	21
5	7

Table [3]. 20 combinations of 2 features selected to combine in sets of 3

Percentage of correct classification for 30 best combinations in set 1

Percent correct	Feature 1	Feature 2	Feature 3
79.4000	10.0000	21.0000	26.0000
77.6000	5.0000	7.0000	23.0000
77.6000	5.0000	23.0000	11.0000
77.4000	5.0000	23.0000	21.0000
76.4000	16.0000	24.0000	18.0000
76.4000	5.0000	23.0000	19.0000
75.8000	23.0000	24.0000	19.0000
75.8000	23.0000	24.0000	15.0000
75.8000	5.0000	23.0000	7.0000
75.6000	5.0000	7.0000	22.0000
75.6000	5.0000	7.0000	21.0000
75.6000	5.0000	7.0000	16.0000
75.4000	5.0000	7.0000	14.0000
75.4000	5.0000	11.0000	10.0000
75.2000	10.0000	21.0000	19.0000
75.2000	8.0000	18.0000	6.0000
75.2000	5.0000	23.0000	2.0000
75.0000	10.0000	21.0000	16.0000
75.0000	10.0000	21.0000	8.0000
75.0000	5.0000	11.0000	18.0000
75.0000	4.0000	26.0000	14.0000
75.0000	5.0000	23.0000	29.0000
75.0000	5.0000	23.0000	25.0000
74.8000	10.0000	21.0000	9.0000
74.6000	10.0000	21.0000	12.0000
74.6000	5.0000	11.0000	23.0000
74.6000	10.0000	24.0000	9.0000
74.6000	5.0000	23.0000	10.0000
74.6000	5.0000	23.0000	9.0000
74.4000	5.0000	7.0000	19.0000

Table [4.1] Results of combinations of 3 features

Percentage of correct classification for 30 best combinations in set 2

Percent correct	Feature 1	Feature 2	Feature 3
79.8000	20.0000	24.0000	12.0000
78.6000	24.0000	30.0000	19.0000
78.6000	4.0000	15.0000	28.0000
78.0000	24.0000	27.0000	19.0000
77.8000	4.0000	17.0000	19.0000
77.6000	8.0000	18.0000	4.0000
77.4000	4.0000	27.0000	19.0000
77.4000	5.0000	23.0000	21.0000
77.2000	5.0000	23.0000	29.0000
77.2000	4.0000	15.0000	27.0000
77.0000	4.0000	27.0000	18.0000
77.0000	4.0000	15.0000	21.0000
76.6000	5.0000	7.0000	23.0000
76.6000	20.0000	24.0000	3.0000
76.4000	16.0000	24.0000	30.0000
76.4000	4.0000	27.0000	25.0000
76.4000	24.0000	27.0000	10.0000
76.4000	23.0000	24.0000	30.0000
76.2000	5.0000	23.0000	3.0000
76.2000	4.0000	17.0000	2.0000
76.2000	4.0000	15.0000	26.0000
75.8000	5.0000	7.0000	15.0000
75.8000	24.0000	30.0000	4.0000
75.8000	5.0000	23.0000	28.0000
75.6000	4.0000	27.0000	15.0000
75.6000	24.0000	27.0000	26.0000
75.6000	24.0000	27.0000	1.0000
75.6000	20.0000	24.0000	25.0000
75.6000	24.0000	30.0000	16.0000
75.4000	4.0000	15.0000	8.0000

Table [4.2] Results of combinations of 3 features

Percentage of correct classification for 30 best combinations in set 3

Percent correct	Feature 1	Feature 2	Feature 3
85.2000	9.0000	24.0000	19.0000
85.0000	9.0000	24.0000	22.0000
84.2000	16.0000	24.0000	19.0000
84.0000	17.0000	24.0000	9.0000
84.0000	4.0000	26.0000	17.0000
83.6000	4.0000	26.0000	11.0000
83.6000	4.0000	17.0000	9.0000
83.6000	24.0000	26.0000	17.0000
83.6000	4.0000	15.0000	9.0000
83.4000	5.0000	11.0000	24.0000
83.4000	9.0000	24.0000	21.0000
83.4000	9.0000	24.0000	17.0000
83.4000	9.0000	24.0000	14.0000
83.4000	4.0000	26.0000	9.0000
83.2000	16.0000	24.0000	1.0000
83.2000	4.0000	17.0000	26.0000
83.2000	24.0000	26.0000	9.0000
83.0000	9.0000	24.0000	12.0000
83.0000	9.0000	24.0000	6.0000
83.0000	4.0000	17.0000	11.0000
82.8000	9.0000	24.0000	18.0000
82.8000	23.0000	24.0000	1.0000
82.8000	4.0000	17.0000	24.0000
82.8000	4.0000	17.0000	8.0000
82.6000	17.0000	24.0000	19.0000
82.4000	17.0000	24.0000	8.0000
82.4000	9.0000	24.0000	2.0000
82.4000	5.0000	23.0000	29.0000
82.2000	5.0000	23.0000	10.0000
82.0000	9.0000	24.0000	26.0000

Table [4.3] Results of combinations of 3 features

Percentage of correct classification for 30 best combinations on average

Percent correct	Feature 1	Feature 2	Feature 3
78.2000	5.0000	23.0000	29.0000
77.6000	5.0000	7.0000	23.0000
77.3333	5.0000	23.0000	21.0000
76.6000	5.0000	23.0000	10.0000
76.0000	23.0000	24.0000	15.0000
75.8667	5.0000	7.0000	21.0000
75.8667	5.0000	23.0000	7.0000
75.6667	5.0000	23.0000	11.0000
75.6000	8.0000	18.0000	4.0000
75.5333	4.0000	17.0000	19.0000
75.5333	5.0000	11.0000	17.0000
75.5333	24.0000	26.0000	14.0000
75.4667	5.0000	23.0000	28.0000
75.4667	4.0000	15.0000	26.0000
75.3333	17.0000	24.0000	19.0000
75.3333	5.0000	23.0000	25.0000
75.2000	5.0000	7.0000	17.0000
75.2000	4.0000	15.0000	23.0000
75.0000	5.0000	23.0000	17.0000
74.9333	5.0000	23.0000	3.0000
74.8667	4.0000	26.0000	15.0000
74.8000	23.0000	24.0000	19.0000
74.8000	5.0000	23.0000	14.0000
74.8000	5.0000	23.0000	1.0000
74.8000	24.0000	26.0000	25.0000
74.7333	24.0000	30.0000	19.0000
74.7333	5.0000	23.0000	19.0000
74.7333	5.0000	23.0000	9.0000
74.6667	5.0000	7.0000	22.0000
74.6667	4.0000	26.0000	19.0000

Table [4.4] Results of combinations of 3 features

4	17	26
5	23	29
9	19	24
4	5	9
5	10	23
5	21	23
4	8	18
19	24	30
5	7	23
19	23	24
9	14	24
4	15	28
5	11	17
4	19	17
5	23	24
5	7	21
5	11	23
14	24	26
10	21	26
4	11	26

Table [5]. 20 combinations of 3 features selected to combine in sets of 4

Percentage of correct classification for 30 best combinations in set 1

Percent correct	Feature 1	Feature 2	Feature 3	Feature 4
81.0000	5.0000	21.0000	23.0000	9.0000
80.6000	5.0000	7.0000	23.0000	6.0000
80.2000	5.0000	21.0000	23.0000	11.0000
79.6000	5.0000	21.0000	23.0000	10.0000
79.4000	5.0000	7.0000	23.0000	12.0000
79.4000	5.0000	10.0000	23.0000	21.0000
79.0000	5.0000	7.0000	23.0000	28.0000
79.0000	5.0000	7.0000	23.0000	19.0000
79.0000	5.0000	21.0000	23.0000	26.0000
78.8000	5.0000	11.0000	23.0000	7.0000
78.6000	5.0000	21.0000	23.0000	12.0000
78.4000	5.0000	21.0000	23.0000	15.0000
78.4000	5.0000	10.0000	23.0000	8.0000
78.0000	5.0000	11.0000	23.0000	21.0000
78.0000	5.0000	7.0000	23.0000	20.0000
78.0000	5.0000	7.0000	23.0000	14.0000
77.8000	5.0000	7.0000	23.0000	2.0000
77.8000	5.0000	21.0000	23.0000	28.0000
77.8000	5.0000	21.0000	23.0000	6.0000
77.8000	5.0000	21.0000	23.0000	3.0000
77.8000	5.0000	23.0000	29.0000	26.0000
77.8000	5.0000	23.0000	29.0000	22.0000
77.6000	10.0000	21.0000	26.0000	2.0000
77.6000	5.0000	7.0000	23.0000	22.0000
77.6000	5.0000	10.0000	23.0000	19.0000
77.6000	5.0000	23.0000	29.0000	19.0000
77.6000	5.0000	23.0000	29.0000	1.0000
77.4000	10.0000	21.0000	26.0000	9.0000
77.4000	5.0000	11.0000	23.0000	10.0000
77.4000	5.0000	11.0000	23.0000	8.0000

Table [6.1] Results of combinations of 4 features

Percentage of correct classification for 30 best combinations in set 2

Percent correct	Feature 1	Feature 2	Feature 3	Feature 4
81.0000	5.0000	23.0000	29.0000	14.0000
79.8000	5.0000	10.0000	23.0000	21.0000
79.6000	5.0000	21.0000	23.0000	11.0000
79.4000	14.0000	24.0000	26.0000	19.0000
79.4000	5.0000	21.0000	23.0000	9.0000
79.2000	5.0000	21.0000	23.0000	13.0000
79.0000	5.0000	11.0000	23.0000	3.0000
79.0000	5.0000	23.0000	29.0000	21.0000
78.8000	5.0000	23.0000	29.0000	6.0000
78.6000	4.0000	19.0000	17.0000	25.0000
78.6000	5.0000	21.0000	23.0000	10.0000
78.4000	4.0000	19.0000	17.0000	6.0000
78.4000	5.0000	23.0000	29.0000	19.0000
78.2000	5.0000	11.0000	23.0000	25.0000
78.2000	5.0000	11.0000	23.0000	6.0000
78.2000	4.0000	15.0000	28.0000	27.0000
78.2000	5.0000	7.0000	23.0000	11.0000
78.2000	19.0000	24.0000	30.0000	11.0000
78.0000	5.0000	21.0000	23.0000	27.0000
77.8000	19.0000	24.0000	30.0000	23.0000
77.8000	19.0000	24.0000	30.0000	16.0000
77.8000	5.0000	10.0000	23.0000	11.0000
77.6000	4.0000	19.0000	17.0000	3.0000
77.6000	5.0000	7.0000	23.0000	28.0000
77.4000	14.0000	24.0000	26.0000	20.0000
77.4000	5.0000	21.0000	23.0000	30.0000
77.2000	5.0000	11.0000	23.0000	8.0000
77.2000	4.0000	19.0000	17.0000	11.0000
77.2000	5.0000	7.0000	23.0000	26.0000
77.2000	5.0000	21.0000	23.0000	12.0000

Table [6.2] Results of combinations of 4 features

Percentage of correct classification for 30 best combinations in set 3

Percent correct	Feature 1	Feature 2	Feature 3	Feature 4
87.4000	9.0000	19.0000	24.0000	14.0000
87.2000	9.0000	14.0000	24.0000	19.0000
87.0000	9.0000	19.0000	24.0000	11.0000
86.8000	9.0000	19.0000	24.0000	18.0000
86.6000	5.0000	21.0000	23.0000	29.0000
86.6000	9.0000	19.0000	24.0000	16.0000
86.4000	9.0000	19.0000	24.0000	21.0000
86.4000	4.0000	17.0000	26.0000	18.0000
86.2000	4.0000	11.0000	26.0000	24.0000
86.2000	4.0000	8.0000	18.0000	9.0000
86.2000	9.0000	19.0000	24.0000	22.0000
86.2000	9.0000	19.0000	24.0000	6.0000
86.0000	9.0000	19.0000	24.0000	12.0000
86.0000	9.0000	19.0000	24.0000	10.0000
85.8000	9.0000	19.0000	24.0000	26.0000
85.8000	4.0000	17.0000	26.0000	9.0000
85.6000	5.0000	7.0000	21.0000	16.0000
85.6000	5.0000	7.0000	21.0000	8.0000
85.6000	9.0000	19.0000	24.0000	8.0000
85.6000	9.0000	19.0000	24.0000	5.0000
85.6000	9.0000	19.0000	24.0000	1.0000
85.4000	9.0000	14.0000	24.0000	4.0000
85.4000	5.0000	21.0000	23.0000	1.0000
85.2000	4.0000	19.0000	17.0000	10.0000
85.2000	9.0000	19.0000	24.0000	4.0000
85.0000	5.0000	11.0000	17.0000	4.0000
85.0000	9.0000	19.0000	24.0000	2.0000
85.0000	4.0000	17.0000	26.0000	8.0000
84.8000	4.0000	11.0000	26.0000	9.0000
84.8000	5.0000	21.0000	23.0000	22.0000

Table [6.3] Results of combinations of 4 features

Percentage of correct classification for 30 best combinations on average

Percent correct	Feature 1	Feature 2	Feature 3	Feature 4
81.0667	5.0000	21.0000	23.0000	9.0000
79.9333	5.0000	23.0000	29.0000	21.0000
79.8667	5.0000	21.0000	23.0000	11.0000
79.6000	5.0000	10.0000	23.0000	21.0000
79.2667	5.0000	23.0000	29.0000	19.0000
79.1333	5.0000	21.0000	23.0000	10.0000
79.0667	5.0000	23.0000	29.0000	14.0000
79.0000	14.0000	24.0000	26.0000	19.0000
78.9333	5.0000	7.0000	23.0000	12.0000
78.8667	5.0000	21.0000	23.0000	22.0000
78.8667	5.0000	7.0000	23.0000	28.0000
78.7333	5.0000	7.0000	23.0000	6.0000
78.6667	5.0000	21.0000	23.0000	7.0000
78.5333	5.0000	21.0000	23.0000	1.0000
78.4667	5.0000	23.0000	29.0000	1.0000
78.4000	5.0000	7.0000	21.0000	8.0000
78.4000	5.0000	7.0000	23.0000	26.0000
78.2667	5.0000	7.0000	23.0000	11.0000
78.2000	5.0000	7.0000	23.0000	22.0000
78.2000	5.0000	23.0000	29.0000	28.0000
78.1333	5.0000	11.0000	23.0000	10.0000
78.1333	5.0000	10.0000	23.0000	25.0000
78.0667	5.0000	7.0000	23.0000	16.0000
78.0000	5.0000	7.0000	23.0000	20.0000
77.8667	5.0000	10.0000	23.0000	29.0000

Table [6.4] Results of combinations of 4 features

k	Correct classification	Performance Index
1	73	0.5196
2	74	0.5099
3	77	0.4796
4	77	0.4796
5	82	0.42
6	81	0.4359
7	76	0.4899
8	80	0.4472
9	79	0.4583
10	79	0.4583

Table[7.1] Classification results with changing K for the crisp classifier for set 1

k	Correct classification	Performance Index
1	74	0.5099
2	74	0.5099
3	77	0.4796
4	77	0.4796
5	74	0.5099
6	76	0.4899
7	76	0.4899
8	75	0.5000
9	78	0.4690
10	78	0.4690

Table[7.2] Classification results with changing K for the crisp classifier for set 2

k	Correct classification	Performance Index
1	79	0.4583
2	79	0.4583
3	81	0.4359
4	84	0.4000
5	83	0.4123
6	85	0.3873
7	81	0.4359
8	81	0.4359
9	82	0.4243
10	82	0.4243

Table[7.3] Classification results with changing K for the crisp classifier for set 3

k	Correct classification	Performance Index
1	75.3333	0.4959
2	75.6667	0.4927
3	78.3333	0.4650
4	79.3333	0.4531
5	79.6667	0.4474
6	80.6667	0.4377
7	77.6667	0.4719
8	78.6667	0.4610
9	79.6667	0.4505
10	79.6667	0.4505

Table[7.4] Average classification results with changing K for the crisp classifier

	percent classification						performanc e index
k \ Threshold	0.3	0.4	0.5	0.6	0.7	0.8	
1	73	73	73	73	73	73	0.5196
2	77	75	73	74	72	73	0.4267
3	75	74	77	75	73	69	0.4261
4	75	74	76	77	76	69	0.4157
5	74	74	81	79	76	73	0.4061
6	69	74	78	79	76	74	0.3993
7	70	74	77	81	77	72	0.3980
8	70	75	79	79	79	72	0.3977
9	69	72	78	80	79	71	0.3971
10	68	73	78	79	79	70	0.3978

Table[8.1] Classification results for the fuzzy classifier for set 1

	percent classification						performance index
k \ Threshold	0.3	0.4	0.5	0.6	0.7	0.8	
1	74	74	74	74	74	74	0.5099
2	72	75	74	77	78	77	0.4328
3	73	75	79	79	77	73	0.4316
4	73	75	79	76	76	72	0.4262
5	71	76	76	78	77	74	0.4176
6	72	73	76	79	75	72	0.4164
7	71	73	79	79	77	70	0.4092
8	69	74	78	80	77	70	0.4099
9	73	75	80	79	77	70	0.4059
10	72	73	81	79	76	72	0.4004

Table[8.2] Classification results for the fuzzy classifier for set 2

	percent classification						performance index
k \ Threshold	0.3	0.4	0.5	0.6	0.7	0.8	
1	79	79	79	79	79	79	0.4583
2	73	76	79	84	84	84	0.3991
3	72	75	81	85	85	82	0.3862
4	75	78	84	86	86	83	0.3704
5	74	80	83	86	86	84	0.3635
6	75	82	85	87	85	83	0.3588
7	74	80	82	84	84	82	0.3605
8	73	78	83	84	84	81	0.3638
9	73	79	83	84	85	81	0.3625
10	73	80	83	84	85	82	0.3615

Table[8.3] Classification results for the fuzzy classifier for set 3

	percent classification						performanc e index
k \ Threshold	0.3	0.4	0.5	0.6	0.7	0.8	
1	75.33	75.33	75.33	75.33	75.33	75.33	0.4959
2	74	75.33	75.33	78.33	78	78	0.4195
3	73.33	74.67	79	79.67	78.33	74.67	0.4146
4	74.33	75.67	79.67	79.67	79.33	74.67	0.4041
5	73	76.67	80	81	79.67	77	0.3957
6	72	76.33	79.67	81.67	78.67	76.33	0.3915
7	71.67	75.67	79.33	81.33	79.33	74.67	0.3892
8	70.67	75.67	80	81	80	74.33	0.3905
9	71.67	75.33	80.33	81	80.33	74	0.3885
10	71	75.33	80.67	80.67	80	74.67	0.3866

Table[8.3] Average classification results with for the fuzzy classifier

File	Membership	Defuzzified	Result
1.0000	0.2736	0	
2.0000	0.3339	0	
3.0000	0.5397	0	0
4.0000	0.5450	0	
5.0000	0.7423	1.0000	
6.0000	0.1732	0	0
7.0000	0.8901	1.0000	
8.0000	1.0000	1.0000	1 Misclassified
9.0000	0.5376	0	
10.0000	0.1742	0	
11.0000	0.4366	0	0
12.0000	0.3458	0	
13.0000	0.5145	0	
14.0000	0.5178	0	0
15.0000	0.1016	0	
16.0000	0	0	
17.0000	0	0	0
18.0000	0.1334	0	0
19.0000	0	0	
20.0000	0	0	
21.0000	0.2923	0	0
22.0000	0	0	
23.0000	0	0	
24.0000	0.1607	0	0
25.0000	0	0	
26.0000	0.4421	0	
27.0000	1.0000	1.0000	0
28.0000	0.3307	0	
29.0000	0.0583	0	
30.0000	0.4965	0	0
31.0000	0.3505	0	
32.0000	0.1181	0	
33.0000	0.2101	0	0

Table [9.1] Classification of the files of set 1

File	Membership	Defuzzified	Result
34.0000	0.5970	0	
35.0000	0	0	
36.0000	0.1193	0	0
37.0000	0.3174	0	
38.0000	0.8117	1.0000	
39.0000	0.0997	0	0
40.0000	0.1889	0	
41.0000	0.4215	0	
42.0000	0.1635	0	0
43.0000	0.6474	1.0000	
44.0000	0	0	
45.0000	0.5495	0	0
46.0000	0.1115	0	0
47.0000	0	0	
48.0000	0.3986	0	
49.0000	0	0	
50.0000	0	0	0
51.0000	0.6709	1.0000	
52.0000	1.0000	1.0000	
53.0000	0.5297	0	1
54.0000	0.7245	1.0000	
55.0000	0.9200	1.0000	
56.0000	1.0000	1.0000	1
57.0000	0.9105	1.0000	
58.0000	0.9398	1.0000	
59.0000	0.5657	0	1
60.0000	0.8968	1.0000	
61.0000	1.0000	1.0000	
62.0000	0.2793	0	
63.0000	0.1088	0	0 **Misclassified**
64.0000	0.6245	1.0000	
65.0000	0.8643	1.0000	
66.0000	0.5054	0	1

Table [9.1] Continued

File	Membership	Defuzzified	Result
67.0000	0.8498	1.0000	
68.0000	0.6969	1.0000	
69.0000	0.8397	1.0000	1
70.0000	0.2901	0	
71.0000	0.8291	1.0000	
72.0000	0.3982	0	0 Misclassified
73.0000	1.0000	1.0000	
74.0000	0.2463	0	
75.0000	0.8043	1.0000	1
76.0000	0.6676	1.0000	
77.0000	1.0000	1.0000	
78.0000	1.0000	1.0000	1
79.0000	1.0000	1.0000	
80.0000	0.7538	1.0000	
81.0000	1.0000	1.0000	1
82.0000	1.0000	1.0000	
83.0000	0.8378	1.0000	
84.0000	1.0000	1.0000	1
85.0000	0.8926	1.0000	
86.0000	0.5448	0	
87.0000	0.5751	0	0 Misclassified
88.0000	0.8273	1.0000	
89.0000	0.2945	0	
90.0000	0.9110	1.0000	1
91.0000	1.0000	1.0000	
92.0000	1.0000	1.0000	
93.0000	0	0	1
94.0000	0.2887	0	
95.0000	0.2079	0	
96.0000	0.5793	0	0 Misclassified
97.0000	1.0000	1.0000	
98.0000	0.7971	1.0000	
99.0000	0.8708	1.0000	1
100.0000	1.0000	1.0000	1

Table [9.1] Continued

File	Membership	Defuzzified	Result
1.0000	0.2579	0	
2.0000	0.1307	0	
3.0000	0	0	0
4.0000	0.2652	0	
5.0000	0.4345	0	
6.0000	0.1175	0	0
7.0000	1.0000	1.0000	
8.0000	0.7086	1.0000	1 Misclassified
9.0000	0.2856	0	
10.0000	0.2745	0	
11.0000	0.3056	0	0
12.0000	0.2720	0	
13.0000	0.5019	0	
14.0000	0.8871	1.0000	0
15.0000	0.0912	0	
16.0000	0	0	
17.0000	0	0	0
18.0000	0.8334	1.0000	1 Misclassified
19.0000	0	0	
20.0000	0	0	
21.0000	0.5483	0	0
22.0000	0	0	
23.0000	0	0	
24.0000	0.1535	0	0
25.0000	0.4955	0	
26.0000	0.1013	0	
27.0000	1.0000	1.0000	0
28.0000	0.3788	0	
29.0000	0.1638	0	
30.0000	0.0905	0	0
31.0000	0	0	
32.0000	0.1431	0	
33.0000	0.0937	0	0

Table [9.2] Classification of the files of set 2

File	Membership	Defuzzified	Result
34.0000	0	0	
35.0000	0	0	
36.0000	0.1281	0	0
37.0000	0.3690	0	
38.0000	0.5734	0	
39.0000	0.1569	0	0
40.0000	0.3659	0	
41.0000	0.4124	0	
42.0000	0.1704	0	0
43.0000	0.4251	0	
44.0000	0.0664	0	
45.0000	0.5356	0	0
46.0000	0.5084	0	0
47.0000	0.1735	0	
48.0000	0.7512	1.0000	
49.0000	0.5115	0	
50.0000	0.0976	0	0
51.0000	0.6361	1.0000	
52.0000	0.8482	1.0000	1
53.0000	0.3471	0	
54.0000	0.8822	1.0000	
55.0000	1.0000	1.0000	1
56.0000	1.0000	1.0000	
57.0000	1.0000	1.0000	
58.0000	0.8730	1.0000	1
59.0000	0	0	
60.0000	0.0389	0	
61.0000	0.3643	0	0 Misclassified
62.0000	1.0000	1.0000	
63.0000	0.8174	1.0000	
64.0000	0.8875	1.0000	1
65.0000	0.7995	1.0000	
66.0000	0.5919	0	
67.0000	0.7533	1.0000	1

Table [9.2] Continued

File	Membership	Defuzzified	Result
68.0000	0.7337	1.0000	
69.0000	0.8524	1.0000	
70.0000	0.8602	1.0000	1
71.0000	0.2217	0	
72.0000	1.0000	1.0000	
73.0000	0.1268	0	0 Misclassified
74.0000	0.8860	1.0000	
75.0000	0.2121	0	
76.0000	0.1684	0	
77.0000	0.6903	1.0000	0 Misclassified
78.0000	0.7680	1.0000	
79.0000	0.8735	1.0000	
80.0000	0.8013	1.0000	1
81.0000	0.1748	0	
82.0000	0.5428	0	
83.0000	0.8496	1.0000	0 Misclassified
84.0000	0.3444	0	
85.0000	0.8298	1.0000	
86.0000	0.8590	1.0000	1
87.0000	0.6879	1.0000	
88.0000	0.9082	1.0000	
89.0000	0.6653	1.0000	1
90.0000	0.1636	0	
91.0000	0.8754	1.0000	
92.0000	0.8594	1.0000	1
93.0000	0.5185	0	
94.0000	0.4932	0	
95.0000	0.7802	1.0000	0 Misclassified
96.0000	0.8684	1.0000	
97.0000	0.8788	1.0000	
98.0000	1.0000	1.0000	1
99.0000	1.0000	1.0000	
100.0000	0.8669	1.0000	1

Table [9.2] Continued

File	Membership	Defuzzified	Result
1.0000	0.3986	0	
2.0000	0.2845	0	
3.0000	0.2562	0	0
4.0000	0.2786	0	
5.0000	0.3226	0	
6.0000	0	0	0
7.0000	1.0000	1.0000	
8.0000	0.5055	0	
9.0000	0.1434	0	0
10.0000	0	0	
11.0000	0	0	0
12.0000	0.0691	0	
13.0000	0.4744	0	
14.0000	0.4708	0	0
15.0000	0	0	
16.0000	0	0	
17.0000	0	0	0
18.0000	0.4623	0	0
19.0000	0	0	
20.0000	0	0	
21.0000	0.2096	0	0
22.0000	0	0	
23.0000	0	0	
24.0000	0.0516	0	0
25.0000	0.2885	0	
26.0000	0.0981	0	
27.0000	0.9336	1.0000	0
28.0000	0.2254	0	
29.0000	0.1465	0	
30.0000	0.0680	0	0
31.0000	0	0	
32.0000	0	0	
33.0000	0.0939	0	0

Table [9.3] Classification of the files of set 3

File	Membership	Defuzzified	Result
34.0000	0.3917	0	
35.0000	0	0	
36.0000	0	0	0
37.0000	0.1689	0	
38.0000	0.5220	0	
39.0000	0	0	0
40.0000	0.0969	0	
41.0000	0	0	
42.0000	0	0	0
43.0000	0.4810	0	
44.0000	0.3154	0	
45.0000	0.4552	0	0
46.0000	0.3285	0	0
47.0000	0.3690	0	
48.0000	0.5593	0	
49.0000	0.3522	0	
50.0000	0.2325	0	0
51.0000	1.0000	1.0000	
52.0000	0.9052	1.0000	
53.0000	0.8115	1.0000	1
54.0000	0.8397	1.0000	
55.0000	0.8754	1.0000	
56.0000	0.0930	0	1
57.0000	0.8330	1.0000	
58.0000	1.0000	1.0000	1
59.0000	1.0000	1.0000	
60.0000	1.0000	1.0000	
61.0000	1.0000	1.0000	1
62.0000	1.0000	1.0000	
63.0000	0.6496	1.0000	
64.0000	0.5075	0	1
65.0000	0.0823	0	
66.0000	0.7810	1.0000	
67.0000	0.2356	0	0 **Misclassified**

Table [9.3] Continued

File	Membership	Defuzzified	Result
68.0000	1.0000	1.0000	
69.0000	1.0000	1.0000	
70.0000	1.0000	1.0000	1
71.0000	1.0000	1.0000	
72.0000	1.0000	1.0000	
73.0000	1.0000	1.0000	1
74.0000	1.0000	1.0000	
75.0000	1.0000	1.0000	
76.0000	1.0000	1.0000	1
77.0000	1.0000	1.0000	
78.0000	1.0000	1.0000	
79.0000	1.0000	1.0000	1
80.0000	0.6068	1.0000	
81.0000	0.9054	1.0000	
82.0000	0.4134	0	1
83.0000	1.0000	1.0000	
84.0000	0	0	
85.0000	0.2914	0	0 Misclassified
86.0000	1.0000	1.0000	
87.0000	1.0000	1.0000	
88.0000	0.8786	1.0000	1
89.0000	0.9018	1.0000	
90.0000	1.0000	1.0000	
91.0000	1.0000	1.0000	1
92.0000	1.0000	1.0000	
93.0000	0.9135	1.0000	
94.0000	0.8292	1.0000	1
95.0000	0.7423	1.0000	
96.0000	1.0000	1.0000	
97.0000	0.0902	0	1
98.0000	0.2564	0	
99.0000	0	0	
100.0000	0.4387	0	0 Misclassified

Table [9.3] Continued

Non deceptive	Deceptive 1	Deceptive 2	Deceptive 3
QQ8R9OIO.011	QQ4Q1O83.011	QQ7LX5Q0.021	QQ8RAJ0C.011
QQ8R9OIO.021	QQ4Q1O83.021	QQ7LX5Q0.031	QQ8RAJ0C.021
QQ8R9OIO.031	QQ4Q1O83.031	QQ7MN2Y0.011	QQ8RAJ0C.031
QQ95LU1T.011	QQ4Q3MDC.011	QQ7MN2Y0.021	QQ9EUKVT.011
QQ95LU1T.021	QQ4Q3MDC.021	QQ7MN2Y0.031	QQ9EUKVT.021
QQ95LU1T.031	QQ4Q3MDC.031	QQ7TC5UF.011	QQ9EUKVT.031
QQAURNUS.021	QQ51DE36.011	QQ7TC5UF.021	QQ9IOOXO.021
QQAURNUS.031	QQ51DE36.021	QQ7TC5UF.031	QQ9IOOXO.041
QQAV53P6.011	QQ51DE36.041	QQ7TQVER.011	QQ9SOW8L.011
QQAV53P6.021	QQ6RQGH6.011	QQ7TQVER.021	QQ9SOW8L.021
QQAV53P6.031	QQ6RQGH6.021	QQ7TQVER.031	QQ9SOW8L.031
QQBQ4SHI.011	QQ6RQGH6.031	QQ7TVADC.011	QQ9SQIK9.011
QQBQ4SHI.021	QQ6RQGH6.041	QQ7TVADC.021	QQ9SQIK9.021
QQBQ4SHI.031	QQ6T711O.011	QQ7TVADC.031	QQ9SQIK9.031
QQBSS7WT.011	QQ6T711O.021	QQ7U2T4R.011	QQ9W0B9F.011
QQBSS7WT.021	QQ6T711O.031	QQ7U2T4R.021	QQ9W0B9F.031
QQBSS7WT.031	QQ6Z59IG.011	QQ7U2T4R.031	QQ9W0B9F.041
QQ7OXM60.021	QQ6Z59IG.021	QQ7YP7QU.011	QQ9U4FMU.011
QQ7RH0RO.011	QQ6Z59IG.031	QQ7YP7QU.021	QQ9U4FMU.021
QQ7RH0RO.021	QQ7PP9B9.011	QQ7YP7QU.031	QQ9U4FMU.031
QQ7RH0RO.031	QQ7PP9B9.021	QQ7YZOJ3.011	QQ9Y_SVF.011
QQ7R51P9.011	QQ7PP9B9.031	QQ7YZOJ3.021	QQ9Y_SVF.021
QQ7R51P9.021	QQ7PDU1X.011	QQ7YZOJ3.031	QQ9Y_SVF.031
QQ7R51P9.031	QQ7PDU1X.021	QQ8_0DPT.011	QQ9YH3QF.011
QQ9TDSP3.011	QQ7PDU1X.031	QQ8_0DPT.021	QQ9YH3QF.021
QQ9TDSP3.021	QQ7_PIPF.011	QQ8_0DPT.031	QQ9YH3QF.031
QQ9TDSP3.031	QQ7_PIPF.021	QQ8_0DPT.041	QQA2TT4C.011
QQA8OWOI.011	QQ7_PIPF.031	QQ8_2UQ9.011	QQA2TT4C.021
QQA8OWOI.021	QQ7_JT70.011	QQ8_2UQ9.021	QQA2TT4C.031
QQA8OWOI.031	QQ7_JT70.021	QQ8_2UQ9.031	QQA3HIRX.011
QQBT22O6.011	QQ7_JT70.031	QQ800IG6.011	QQA3HIRX.021
QQBT22O6.021	QQ738DYX.011	QQ800IG6.021	QQA3HIRX.031
QQBT22O6.031	QQ738DYX.021	QQ800IG6.031	QQA32UTF.011
QQBO9O_9.011	QQ738DYX.031	QQ82OIU9.011	QQA32UTF.021
QQBO9O_9.021	QQ75ULP9.011	QQ82OIU9.021	QQA32UTF.031
QQBO9O_9.031	QQ75ULP9.021	QQ82OIU9.031	QQA6U_IF.011
QQBC7PP6.011	QQ75ULP9.031	QQ82SUTX.011	QQA6U_IF.031
QQBC7PP6.021	QQ79_EYF.011	QQ82SUTX.021	QQA6U_IF.041
QQBC7PP6.031	QQ79_EYF.021	QQ82SUTX.031	QQAM4E3L.011
QQCHCK_O.011	QQ79_EYF.031	QQ860ZNU.011	QQAM4E3L.021
QQCHCK_O.021	QQ7BGDML.011	QQ860ZNU.021	QQAM4E3L.031
QQCHCK_O.031	QQ7BGDML.021	QQ860ZNU.031	QQARF2_X.011
QQCDTKP0.011	QQ7BGDML.031	QQ89U_ZR.011	QQARF2_X.021
QQCDTKP0.031	QQ7ETC8I.011	QQ89U_ZR.021	QQARF2_X.031
QQCDTKP0.041	QQ7ETC8I.021	QQ89U_ZR.031	QQAWA38X.011
QQCM5Y56.011	QQ7ETC8I.031	QQ8ATU26.011	QQAWA38X.021
QQCQQT8Y.011	QQ7JAQCS.011	QQ8ATU26.021	QQAWA38X.031
QQCQQT8Y.021	QQ7JAQCS.021	QQ8ATU26.031	QQAYXZGU.011
QQCQQT8Y.031	QQ7JAQCS.031	QQ8FGMVI.011	QQAYXZGU.021
QQCQQT8Y.041	QQ7LX5Q0.011	QQ8FGMVI.021	QQAYXZGU.031

Table [10] NSA Polygraph files used in sets 1-3.

Note: Each set consists of non-deceptive files and one of the deceptive sets

Appendix B:
Program Listings

Classify Program

```
% This is a Matlab program
% This script parses a matrix of polygraph
% vectors into training and testing vectors.
% It then calls the classifier, trains, tests
% and gives results.


c = 2;                  % number of classes
percent_train=.75;          % percentage of inputs used for training

features=[1]                % features to use
classification=1;  % use fuzzy classifier
kk=5;                       % K in K nearest neighbor
change=1;                   % Randomize training and testing inputs
repeat=20;                  % Number of repeatitions
ut=.5;                      % Upper threshhold for 3 class fuzzy classifier
lt=.5;                      % Lower threshhold for 3 class fuzzy classifier

load set31;                   % file containing feature matrix
                                  % and vector that indicates whether
                                     % column is truthful or deceptive
%classvect;                           % vector of classes eg. 1 = deceptive
                       % 0 = truthful vector
featurematrix = featmat;        % matrix of features
dimension = size(featurematrix);
columns = dimension(2);             % the total number of columns in the feature matrix
number_train = round(percent_train*columns);        % number of vectors
                                    % used for training


ur=.5;                      %upper threshold
continue=1;                         % to repeat the program
while (continue==1)
'==================================================================='
apercent_classified=[];             % clear average results
acorrect=[];
acc=[];
ffresult=[];
ccresult=[];
ttestclass=[];

men=0;
while(men ~=7)
        men=menu('Select:','Features','Type','K','Random'...
        ,'Repeat','% training','Start','Defuzz','Exit');

        if (men==1)
        'enter a vector of the features you want tested (eg. [1 2 4]) '
```

```
        features = input(' ');           % features being tested
        end

        if (men==2)
                classification=menu('Type:','Fuzzy','Crisp');
        end

        if (men==3)
        kk = input('enter the "K" in K nearest neighbor   ')
        end

        if (men==4)
                change=menu('Selection','Random','Constant');
        end

        if (men==5)
                repeat=input('Enter number of repeatitions')
        end

        if (men==6)
                percent_train=input('Enter percentage of the files used for training, 1 for all-1')
        end
        if (men==8)
                ch=menu('Defuzzification', '3class', 'Upper thresh','Lower thresh');
                if ch==1,          classification=3,  end
                if ch==2
                        ut=input('enter the upper threshhold'); % lower limit for class 1
                end
                if ch==3
                        lt=input('enter the lower threshhold'); %upper limit for class 0
                end
        end
        if (men==9) break,end
end
if men==9 break,end
number_train = round(percent_train*columns);
acorrect=[];                    % vector for the average of correct classification
acc=[];                         % vector for the average of performance index

if percent_train == 1           % To repeat nonrandom testing for all the files.
        repeat =columns;
end

for trial=1:repeat

featurematrix = featmat(features,:);    % creates a feature matrix of the
                                        % the features being tested
if ( (change==1) & (percent_train~=1) )
        [trainvect, testvect] = randvect(number_train,columns);
end;
if percent_train == 1
        testvect = trial;
        if (trial ==1)
                trainvect=2:columns;
```

```
        end
        if (trial == columns)
                trainvect=1:columns-1;
        end
        if ( trial ~=1  &  trial ~=columns )
                trainvect = [1:trial-1 , trial+1:columns];
        end
end
testvect
trainvect
u = featurematrix(:,testvect);            % testing matrix

testclass = classvect(1,testvect);        % class of each column in testing matrix

p = featurematrix(:,trainvect);           % training matrix

t = classvect(1,trainvect);               % class of each column in training matrix


if classification == 1                    % Fuzzy classifier

        % m = input('enter the degree of fuzziness "M" (1<=M<=infinfity)')
        m = 2;
        save fdatafil c kk m p t u
%       !fknn                             %This line invokes the classifier program in a dos window
        dos('del foutfile.mat|')          %to make sure that the program actulally works
        dos('fknn|')
        'Now loading the result of the fuzzy classifier'
        load foutfile
        '-----------------------------------------------------------'
        kk, features
        fresult
        testclass

        if(percent_train==1)
                ffresult=[ffresult fresult]
                ttestclass=[ttestclass testclass];
        end

        cr =fresult(2,:) > ut             % defuzzification of the result
        correct = 100*(1-mean(abs(testclass-cr)))  % percentage correct classified
        cc = [1-testclass; testclass];    % adding a row of complements to c
        cc=fresult-cc;
        'Performance Index='
        cc = sqrt(mean(mean(cc .^ 2)))
end

if classification == 2                    % crisp classifier

        save cdatafil c kk p t u
%       !cknn             %This line invokes the classifier program in a dos window
        dos('del foutfile.mat|')          %to make sure that the program actulally works
        dos('cknn|')
        'Loading the Crisp output file'
```

```
        load coutfile
        '------------------------------------------------------------'
        kk, features
        cresult
        testclass

        if(percent_train==1)
                ccresult=[ccresult cresult]
                ttestclass=[ttestclass testclass];
        end

        correct = 100*(1-mean(abs(testclass-cresult)))  % percentage correct classified
        cc = sqrt(mean(abs(testclass-cresult)))         % performance index

end
if classification == 3                    % Fuzzy classifier but defuzzification into 3 classes

        % m = input('enter the degree of fuzziness "M" (1<=M<=infinfity)')
        m = 2;
        save fdatafil c kk m p t u
%       !fknn                           %This line invokes the classifier program in a dos window
        dos('del foutfile.mat|')        %to make sure that the program actulally works
        dos('fknn|')
        'Now loading the result of the fuzzy classifier'
        load foutfile
        '------------------------------------------------------------'
        kk, features
        fresult
        testclass

        if(percent_train==1)
                ffresult=[ffresult fresult]
                ttestclass=[ttestclass testclass];
        end
        class1=find(fresult(2,:) >ut);
        class0=find(fresult(2,:) <lt);
        class3=find(fresult(2,:) >lt & fresult(2,:) <ut);
        percent_classified=100*((length(class0)+length(class1))/length(testclass))
        fr=[fresult(:,class1) fresult(:,class0)]         % the section that is classified into one of the two
classes
        cr=fr(2,:)>ut
        tr=[testclass(class1) testclass(class0)]         % the section that is classified into one of the two
classes
        correct = 100*(1-mean(abs(tr-cr)))  % percentage correct classified
        cc = [1-tr; tr];            % adding a row of complements to cc
        cc=fr-cc;
        'Performance Index='
        cc = sqrt(mean(mean(cc .^ 2)))
end

        apercent_classified = [apercent_classified percent_classified]
        acorrect=[acorrect correct]
        acc=[acc cc]
```

```
end                 % for trial

if classification ==3                              % 3 class fuzzy
apercent_classified=mean(apercent_classified)
end
acorrect, mean(acorrect)
acc, mean(acc)

continue=3;
while (continue == 3 | continue==4)
continue=menu('Repeat?', 'Yes', 'no','Plot', 'threshold');
if(continue==3)
        dim=menu('Dimension', 'Two', 'Three')+1;
        if(dim==2)

                pp=p(:,find(t));
                plot(pp(1,:),pp(2,:),'r+');
                title('A clustering of two class data');
                hold on
                pp=p(:,find(t==0));
                plot(pp(1,:), pp(2,:), 'gx');

                pp=u(:, find(testclass));
                plot(pp(1,:), pp(2,:), 'r+');
                pp=u(:,find(testclass==0));
                plot(pp(1,:), pp(2,:), 'gx');

                hold off
        end     %if(dim==2)

        if(dim==3)

                pp=p(:,find(t));
                plot3(pp(1,:),pp(2,:), pp(3,:), 'r+');
                title('A clustering of two class data');
                hold on
                pp=p(:,find(t==0));
                plot3(pp(1,:), pp(2,:), pp(3,:), 'rx');

                pp=u(:, find(testclass));
                plot3(pp(1,:), pp(2,:), pp(3,:), 'g+');
                pp=u(:,find(testclass==0));
                plot3(pp(1,:), pp(2,:), pp(3,:), 'gx');

                hold off
        end     %if(dim==3)

end    %if(continue==3)

if (continue==4)

        ch=menu('Defuzzification', '3class', 'Upper thresh','Lower thresh');
        if ch==1,           classification=3,  end
```

```
        if ch==2
                ut=input('enter the upper threshhold'); % lower limit for class 1
        end
        if ch==3
                lt=input('enter the lower threshhold'); %upper limit for class 0
        end

        if classification==1
                cr =ffresult(2,:) > ut          % defuzzification of the result
                correct = 100*(1-mean(abs(ttestclass-cr)))  % percentage correct classified
                cc = [1-ttestclass; ttestclass];          % adding a row of complements to c
                cc=ffresult-cc;
                'Performance Index='
                cc = sqrt(mean(mean(cc .^ 2)))
        end

        if classification==2
                correct = 100*(1-mean(abs(ttestclass-ccresult)))  % percentage correct classified
                cc = sqrt(mean(abs(ttestclass-ccresult)))        % performance index
        end

        if classification==3
                class1=find(ffresult(2,:) >ut);
                class0=find(ffresult(2,:) <lt);
                class3=find(ffresult(2,:) >lt & ffresult(2,:) <ut);
                fr=[ffresult(:,class1) ffresult(:,class0)]        % the section that is classified into one of
the two classes
                cr=fr(2,:)>ut
                tr=[ttestclass(class1) ttestclass(class0)]        % the section that is classified into one of
the two classes
                percent_classified=100*((length(class0)+length(class1))/length(ttestclass))
                correct = 100*(1-mean(abs(tr-cr)))  % percentage correct classified
                cc = [1-tr; tr];          % adding a row of complements to cc
                cc=fr-cc;
                'Performance Index='
                cc = sqrt(mean(mean(cc .^ 2)))
        end
end

end     % while continue == 3 | 4

end                     % while continue
```

```
/*      This program implements a K-nearest neighbor classifier.
        created by:  Shahab Layeghi

        created:  8/4/93
        last modified: 9/17/93

*/
```

```
/* The main program opens a matlab data file, reads the training matrix,
classifies each entry in the testing matrix, and writes the result in an
output file. The file that this program gets the information from should be
called  "cdatafil.mat". As the name implies it is in matlab file format.
The data in this file should have the following order:

1. A single variable 'C' which is the number of classes.
2. A single variable 'K' which is the parameter 'K' in K-NN Algorithm.
3. A trainig matrix 'P' which contains a set of feature vectors. Each vector
is in a column of the matrix.
4. A classes vector 'T' which contains the classes of the training set
5. An input matrix 'U' which contains a set of unclassified feature vectors.

The main program uses the CrispKNN routine to classify each one of the input
vectors and saves the results (the classes that these inputs belong to) in a
file called coutfile.mat.  This file is in Matlab format.  This file contains
a vector of the classes called:

'cresult'


This program can be called from dos, or within Matlab by using dos escpae
character '!'.  An example Matlab script file that shows how this program can
be used is included in the file "cknntest.m".

*/

#include <stdio.h>
#include <stdlib.h>
#include <time.h>
#include <math.h>
#include <conio.h>

#define INPUTFILE "cdatafil.mat"
#define OUTPUTFILE "coutfile.mat"

// Function Prototypes -----------------------------------------------

int CrispKNN(double *Input, double *Samples, double *Lables);
double FindDistance(double *vec1, double *vec2);
double Maxd(double *vec, int *index, int Length);
int FindMax(int *vector, int *count, int Length, int Max);
int loadmat(FILE * fp,int *type, char *pname, int *mrows, int *ncols,
                    int *imagf, double **preal, double **pimag);
void savemat(FILE *fp, int type, char *pname, int mrows, int ncols,
                    int imagf, double *preal, double *pimag);


// Global variables, these variables will be set by reading matlab file  ------

int classes;          /* the number of classes */
int features;         /* Number of features in a class */
```

```
int KK ;                                        /* K in K-nearest neighbors */
int SampleSize;                                 /* Number of Labled Samples */
int TestSize;

//-----------------------------------------------------------------------

/*--------------------------------------------------------------------*/

void main()
{

        double *Lables;
        double *KP;
        double *input;
        int i,j;
        FILE *fp;
        char name[20];
        int type, imagf;
        double *Samples, *isamples;     // isamples is for imaginary part of the matrix that is not used in
here.
        double *Testdata;
        double *result;
        fp=fopen(INPUTFILE,"rb");
        if(!fp) {
                printf("cannot open the file");
                exit(-1);
        }
        // read classes from the file
        loadmat(fp, &type, name, &i, &j, &imagf, &KP, &isamples);
        if(i!=1 || j!=1) {
                printf("error: You should include classes at the beginning of the file\n");
                exit(-1);
        }
        classes=*KP;

        // read KK from the file
        loadmat(fp, &type, name, &i, &j, &imagf, &KP, &isamples);
        if(i!=1 || j!=1) {
                printf("error: You should include K at the beginning of the file\n");
                exit(-1);
        }
        KK=*KP;

        // read the matrix from the datafile.
        loadmat(fp, &type, name, &features, &SampleSize, &imagf, &Samples, &isamples);

        // reading lables from data file
        loadmat(fp, &type, name, &i, &j, &imagf, &Lables, &isamples);
        if(i!=1 || j!=SampleSize) {
                printf("error: Number of labels is different from the number of samples\n");
                exit(-1);
        }
```

```
	// read data to be classified from the file
	loadmat(fp, &type, name, &i, &TestSize, &imagf, &Testdata, &isamples);
	if(i != features) {
		printf("error: Training and testing matrices should have the same size");
		exit(-1);
	}

	// Allocate space for result vector

	result = (double *) malloc(TestSize*sizeof(double));
	if(!result) {
		printf("Error: cannot allocate memory for the result vector");
		exit(-1);
	}

	for(i=0; i<TestSize; i++) {		// for each input
		input=Testdata+i*features;
		result[i]=CrispKNN(input, Samples, Lables);
//		printf("class: %lf\n", result[i]);
	}
	fclose(fp);
//	printf("\n  End of classification, Now writing the result in the file");

	fp=fopen(OUTPUTFILE, "wb");
	if(!fp) {
		printf("Error: Cannot write the file");
		getch();
	}
	savemat(fp, 0, "cresult", 1, TestSize, 0, result, result);
	fclose(fp);

}

/*------------------------------------------------------------------*/
int CrispKNN(double *Input, double *Samples, double *Lables)
{
	int i,j ;
	int nj, k, nk;
	double *distance;
	int *index;
	double x,y;

	distance = (double *) malloc(KK*sizeof(double));
	if(!distance) {
		printf("Error: Not enough memory for distance vector");
		exit(-1);
	}

	index = (int *) malloc(KK*sizeof(int));
	if(!index) {
		printf("Error: Not enough memory for index vector");
		exit(-1);
	}
```

```
	for(i=0; i<KK; i++) {  // This loop initializes K nearest neighbors to the first K Samples
		index[i]=Lables[i]+1;
		distance[i]=FindDistance(Input, &Samples[i*features]);
	}
	for(i=KK; i<SampleSize; i++) {    // This is the loop that finds the K nearest Neighbors
		x=Maxd(distance, &j, KK);
		y=FindDistance(Input, &Samples[i*features]);
		if(y < x) {  // This sample is closest to the input than the farthest K Neighbors
			distance[j]=y;
			index[j]=Lables[i]+1;
		}
	}
	j=FindMax(index, &nj, KK, classes);   // Finds the class of maximum occurance

	/* In this section it is checked to see if there is a tie.  That is if
	there are two or more classes with the same number of occureances.  If
	there is a tie for two classes,  the class with the minimum sum of
	distances is selected. No action is taken for a tie of more than two
	classes.  */

	for (i=0; i<KK; i++)
		if(index[i]==j) index[i]=0;
	k=FindMax(index, &nk, KK, classes);
	if(nk==nj) {			// If there is a tie.
		x=0;
		for(i=0; i<KK; i++) {
			if(index[i]==0)
				x+=distance[i];
		}
		y=0;
		for(i=0; i<KK; i++) {
			if(index[i]==k)
				y+=distance[i];
		}
		if(y<x)						//If sum of the distances to class j is
less than that of class k
			j=k;
	}

	free(distance);
	free(index);
	return j-1;

}

/*-----------------------------------------------------------------------*/
/* This function returns the Euclidian distance between two vectors */

double FindDistance(double *vec1, double *vec2)
{

	int k;
	double distance;
```

```
        distance = 0;
        for(k=0; k<features; k++) {
                        distance +=(vec1[k]-vec2[k])*(vec1[k]-vec2[k]);
//                      distance += pow(vec1[k]-vec2[k] , 2);
        }
        return distance;
}

/*----------------------------------------------------------------------*/
/* This function finds the biggest element of an array.  It returns that
value and also returns the index to that element in index.
*/

double Maxd(double *vec, int *index, int Length)
{
        int i,j=0;

        j=0;
        for(i=1; i<Length; i++)
                if(vec[i]>vec[j]) j=i;
        *index=j;
        return(vec[j]);
}

/*----------------------------------------------------------------------------*/
/* This function finds a number that is most often repeated in an array of
integer values, and returns that number. Length of array shoud be less than
100.  It is supposed that number is an integer greater than zero.
vector is a pointer to the array.  count is the number of times that the
number is repeated.  Length is the length of the vector.
*/

int FindMax(int *vector, int *count, int Length, int Max)
{

        int i, j, m;
        int t[101];

        if(Max>100) Max=100;
        for(i=0; i<Max+1; i++)
                t[i]=0;
        for(i=0; i<Length; i++)
                t[vector[i]]++;
        m=t[1];
        j=1;
        for(i=1; i<Max+1; i++) {
                if(t[i]>m) {
                        m=t[i];
                        j=i;
                }
        }
        *count=m;
        return (j); }
```

```c
/*      This program implements a fuzzy version of K-nearest neighbor classifier.
        created by: Shahab Layeghi

        created: 9/1/93
        last modified: 9/3/93

*/

/* The main program opens a matlab data file, reads the training matrix,
classifies each entry in the testing matrix, and writes the result in an
output file. The file that this program gets the information from should be
called  "fdatafile.mat". As the name implies it is in matlab file format.
The data in this file should have the following order:

1. A single variable 'C' which is the number of classes.
2. A single variable 'K' which is the parameter 'K' in K-NN Algorithm.
3. A single variable 'M' which is the coefficient in fuzzy algorithm.
4. A trainig matrix 'P' which contains a set of feature vectors. Each vector
is in a column of the matrix.
5. A class membership matrix 'T' which contains the membership values of the
training set vectors to the classes.
6. An input matrix 'U' which contains a set of unclassified feature vectors.

The main program uses the FuzzyKNN routine to classify each one of the input
vectors and saves the results (the classes that these inputs belong to) in a
file called "foutfile.mat". This file is in Matlab format.  This file contains
a single variable called fresult.  It is a vector of the classes.

This program can be called from dos, or within Matlab by using dos escpae
character '!'.  An example Matlab script file that shows how this program can
be used is included in the file "fknntest.m".

*/

#include <stdio.h>
#include <stdlib.h>
#include <time.h>
#include <math.h>
#include <conio.h>

#define INPUTFILE "fdatafil.mat"
#define OUTPUTFILE "foutfile.mat"

// Function Prototypes ----------------------------------------------

void FuzzyKNN(double *Input, double *Samples, double *Lables, double *Result);
double FindDistance(double *vec1, double *vec2);
double Maxd(double *vec, int *index, int Length);
int FindMax(int *vector, int *count, int Length, int Max);
int loadmat(FILE * fp,int *type, char *pname, int *mrows, int *ncols,
                    int *imagf, double **preal, double **pimag);
void savemat(FILE *fp, int type, char *pname, int mrows, int ncols,
```

```
                int imagf, double *preal, double *pimag);


// Global variables, these variables will be set by reading matlab file  ------

int Classes;          /* the number of classes */
int features;         /* Number of features in a class */
int KK ;                                       /* K in K-nearest neighbors */
int SampleSize;                                /* Number of Labled Samples */
int TestSize;
double M;                                                          /* Coefficient in fuzzy
algorithm

//---------------------------------------------------------------------


/*---------------------------------------------------------------------*/

void main()
{

        double *Lables;
        double *KP;
        double *input;
        int i,j;
        FILE *fp;
        char name[20];
        int type, imagf;
        double *Samples, *isamples;    // isamples is for imaginary part of the matrix that is not used in
here.
        double *Testdata;
        double *result;            // pointer to the result matrix
        double *iresult;                       // result vector of classification of a single vector

        fp=fopen(INPUTFILE,"rb");
        if(!fp) {
                printf("cannot open the file");
                exit(-1);
        }
        // read classes from the file
        loadmat(fp, &type, name, &i, &j, &imagf, &KP, &isamples);
        if(i!=1 || j!=1) {
                printf("error: You should include classes at the beginning of the file\n");
                exit(-1);
        }
        Classes=*KP;

        // read KK from the file
        loadmat(fp, &type, name, &i, &j, &imagf, &KP, &isamples);
        if(i!=1 || j!=1) {
                printf("error: You should include K at the beginning of the file\n");
                exit(-1);
        }
        KK=*KP;
```

```
        // read M from the file
        loadmat(fp, &type, name, &i, &j, &imagf, &KP, &isamples);
        if(i!=1 || j!=1) {
                printf("error: You should include M as the thrid parameter\n");
                exit(-1);
        }
        M=*KP;

        // read the matrix from the datafile.
        loadmat(fp, &type, name, &features, &SampleSize, &imagf, &Samples, &isamples);

        // reading lables from data file
        loadmat(fp, &type, name, &i, &j, &imagf, &Lables, &isamples);
        if(i!=1 || j!=SampleSize) {
                printf("error: Number of labels is different from the number of samples\n");
                exit(-1);
        }

        // read data to be classified from the file
        loadmat(fp, &type, name, &i, &TestSize, &imagf, &Testdata, &isamples);
        if(i != features) {
                printf("error: Training and testing matrices should have the same size");
                exit(-1);
        }

        // Allocate space for result vector

        result = (double *) malloc(TestSize*Classes*sizeof(double));
        if(!result) {
                printf("Error: cannot allocate memory for the result Matrix");
                exit(-1);
        }

        for(j=0; j<TestSize; j++) {             // for each input
                input=Testdata+j*features;
                FuzzyKNN(input, Samples, Lables, iresult);
//              printf("\n Memberships:");
                for(i=0; i<Classes; i++) {
                        result[j*Classes+i]=iresult[i];
                        printf(" %lf ", iresult[i]);
                }
        }
        fclose(fp);
//      printf("\n  End of classification, Now writing the result in the file");

        fp=fopen(OUTPUTFILE, "wb");
        if(!fp) {
                printf("Error: Cannot write the file");
                getch();
        }
        savemat(fp, 0, "fresult", Classes, TestSize, 0, result, result);
        fclose(fp);
```

```
}

/*----------------------------------------------------------------*/
/* This is a fuzzy K Nearest neighbor classifier routine. Input is the
vector to be classified, Samples is the matrix of classified samples,
Lables is the vector of the classes that these samples belong to.
Result is the vector of membership values of Input to each class.
*/
void FuzzyKNN(double *Input, double *Samples, double *Lables, double *Result)
{
	int i,j,n ;
	int nj, k, nk;
	double *distance;
	int *index;
	double x,y;
	double *membership;			// pointer to membership matrix
	double nsum, dsum, temp;

	/* This section builds a fuzzy membership matrix from the lables.
	Membership of each sample to the class that it belongs to is assigned
	to 1, and the membership of it to other classes is assigned to 0 */

	membership = (double *) malloc(SampleSize*Classes*sizeof(double));
	if(!membership) {
		printf("Error: Not enough memory for membership matrix");
		exit(-1);
	}
	for(i=0; i<SampleSize*Classes; i++)
		*(membership+i)=0;			// Initializing matrix to zero
	for(j=0; j<SampleSize; j++) {
		i=*(Lables+j);
		*(membership+i*SampleSize+j)=1;
	}

	distance = (double *) malloc(KK*sizeof(double));	// allocate space for the vector
	if(!distance) {
		printf("Error: Not enough memory for distance vector");
		exit(-1);
	}

	index = (int *) malloc(KK*sizeof(int));
	if(!index) {
		printf("Error: Not enough memory for index vector");
		exit(-1);
	}

	for(i=0; i<KK; i++) {	// This loop initializes K nearest neighbors to the first K Samples
		index[i]=i;
		distance[i]=FindDistance(Input, &Samples[i*features]);
	}
	for(i=KK; i<SampleSize; i++) {	// This is the loop that finds the K nearest Neighbors
		x=Maxd(distance, &j, KK);
		y=FindDistance(Input, &Samples[i*features]);
		if(y < x) {	// This sample is closest to the input than the farthest K Neighbors
```

```
                    distance[j]=y;
                    index[j]=i;
            }
        }
        for(j=0; j<Classes; j++) {
            nsum=dsum=0;
            for(n=0; n<KK; n++) {
                i=index[n];
                temp=FindDistance(Input, &Samples[i*features]);
                if(temp < 1e-10)  {                                    //If distance is
zero
                    Result[j]=membership[j*SampleSize+i];
                    break;
                }
                if(M == 2)
                    temp=1/temp;
                else if(M != 1)
                    temp=pow(1/temp, 1/(M-1));
                else
                    temp=0;
                nsum += membership[j*SampleSize+i]*temp;
                dsum += temp;
            }
            if(dsum !=0)
                Result[j]=nsum / dsum;
        }
        free(membership);
        free(distance);
        free(index);
}


/*---------------------------------------------------------------------*/
/* This function returns the Euclidian distance between two vectors */

double FindDistance(double *vec1, double *vec2)
{

        int k;
        double distance;

        distance = 0;
        for(k=0; k<features; k++) {
                distance += (vec1[k]-vec2[k])*(vec1[k]-vec2[k]);
//              distance += pow(vec1[k]-vec2[k] , 2);
        }
        return distance;
}

/*-----------------------------------------------------------------*/
/* This function finds the biggest element of an array.  It returns that
value and also returns the index to that element in index.
*/
```

```
double Maxd(double *vec, int *index, int Length)
{
        int i,j=0;

        j=0;
        for(i=1; i<Length; i++)
                if(vec[i]>vec[j]) j=i;
        *index=j;
        return(vec[j]);
}

/*-----------------------------------------------------------------*/
/* This function finds a number that is most often repeated in an array of
integer values, and returns that number. Length of array shoud be less than
100. It is supposed that number is an integer greater than zero.
vector is a pointer to the array. count is the number of times that the
number is repeated. Length is the length of the vector.
*/

int FindMax(int *vector, int *count, int Length, int Max)
{

        int i, j, m;
        int t[101];

        if(Max>100) Max=100;
        for(i=0; i<Max+1; i++)
                t[i]=0;
        for(i=0; i<Length; i++)
                t[vector[i]]++;
        m=t[1];
        j=1;
        for(i=1; i<Max+1; i++) {
                if(t[i]>m) {
                        m=t[i];
                        j=i;
                }
        }
        *count=m;
        return (j);
}
```

The Use of Fuzzy Set Classification for Pattern Recognition of the Polygraph (Renewal)

Table of Contents

I. Project Summary

Polygraph testing has been used as a technique for measuring deception throughout the twentieth century. Throughout most of this time period the task of interpreting the data has rested solely on the trained examiner. Recently, automated computer evaluation of the polygraph using statistically derived discrimination functions has begun in an effort to aid the polygraph examiner. The purpose of this proposed study is to continue the work begun under ONR Grant N00014-93-1-0570 to investigate the use of fuzzy set classification to perform the data analysis. In that previous study it was shown that fuzzy membership functions can accurately classify the MGQT polygraph data at greater than 90% accuracy levels. This study will focus on optimizing the fuzzy classifier further, test the classifier on Zone Comparison Data as well as MGQT, and adapt the algorithm for use in a real-time testing scenario. At the completion of this project, a software program will be delivered that will perform classification of the polygraph data on an 80486 based personal computer.

II. Project Description

A. Objectives of Proposed Project

The objectives of the proposed project are to:

(1) study the relationship between the fuzzy classifier and the success of classification;

(2) test the optimized algorithm on both MGQT and zone-comparison data;

(3) and investigate the algorithm in a real-time testing scenario.

B. Introduction

1. The Polygraph

The ability to directly measure the signals, both mechanical and electrical, emanating from the living human body has been around for hundreds of years. Ever since the beginning of these observations the interpretation of biological data has been used to understand the physiology, pathology, neurology, and psychology of the living human. In the late 1800's, study began on interpreting biological data in an effort to better understand one particular aspect of human cognitive psychology - deceit (Lombroso, 1895). Specifically, respiration rate, heart rate/blood pressure, and galvanic skin response, measured by a device known as the polygraph, were used to determine whether a person was telling the truth or lying. Over the past 90 years this device has been used with varying degrees of success. Because of its recent and abundant use in criminal investigations and employee screening, the accuracy of the test has become increasingly critical.

Two of the leading causes of failure of the polygraph test to accurately and definitively assess a subject's veracity are the individual administrator's variability in interpreting the polygraph data and the complexity of the interpretation protocols (Office of Technology Assessment, 1983). To overcome this shortcoming of the polygraph test, recent work (see Olsen, 1991) has focused on the use of computers for interpretation of the biological data.

One technique used for computer analysis of the polygraph involves two steps (Olsen, 1991 and Kircher, 1988, for example). First the data is described by approximately 20 parameters (descriptors) which have been determined to be important in the evaluation of the polygraph. Second, this data is evaluated using statistical discriminant analysis to "construct an optimal linear combination of physiological measures for diagnosing truth and deception" (Kircher, 1988). The results of Kircher's work showed that by using a derived discriminating function and arbitrary threshold level, the computer could equal (and actually exceed) the performance of an experienced polygraph examiner. This discriminating function reinforced the observation that the Galvanic Skin Response is the most important indicator of a subjects truthfulness.

Two questions that arise from this type of discriminant analysis are:

1) Is this discriminant function and threshold level optimal for all subjects?

2) Are there other possible descriptors of the polygraph which would yield even more information about the subject's veracity?

The use of fuzzy set theory may shed light on these questions, and in so doing may produce an even more accurate polygraph analysis.

2. Fuzzy Logic

Signals can be generally classified into three categories; deterministic, probabilistic, and possibilistic (fuzzy events). In the case of biological data the patterns are probabilistic or possibilistic because they generally contain a large random component. As mentioned previously, computer scoring of the polygraph relies on *probabilistic* discrimination functions and an arbitrary threshold to classify the data. Fuzzy set theory, however, defines the concept of a *possibilistic* distribution as a fuzzy restriction which acts as an elastic constraint on the values that may be assigned to a variable (Zadeh, 1977). "A fuzzy variable is associated with a possibility distribution in much the same way as a random variable is associated with a probability distribution." (Zadeh, 1977)

The key to fuzzy logic is that classes of objects exist with a continuum of grades of memberships (Zadeh, 1965) so that, unlike probabilistic discrimination functions, no arbitrary threshold is needed. Rather, classification is made according to the degree of membership in a given class. In addition, the membership function itself can be automatically adapted for a given training set composed of data and its corresponding class. This is because the theory of possibility, as compared to the theory of probability, relates to the perception of degrees of evidence instead of degrees of likelihood (Zadeh, 1977).

Figure #1 shows the components of a fuzzy set classification system (Martin, 1982). One can see that the learning mechanism is only active in the adaptation of the partition (membership function). This system operates on a set of data $x_n(t)$ which are extracted from a training set, that is:

$$x(t) = [x_1(t), x_2(t), ..., x_n(t)] \text{ with } 0 < x_i(t) < 1$$

The process of extracting the data set from the training set is completed in the "Signal Processing" step. This step is also known as the data parser.

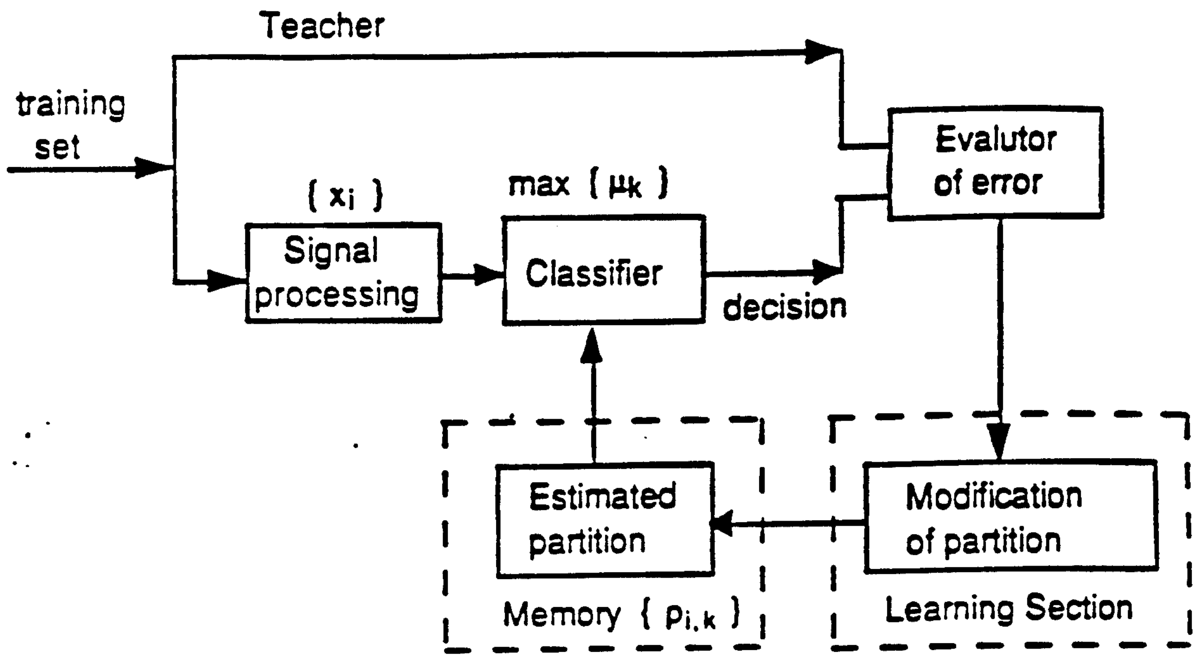

Figure #1: Fuzzy Logic Classification System

For each class C_k, there corresponds a vector of descriptors characterizing the class.

$$\rho_k = [\, \rho_{1,k}, \rho_{2,k}, \cdots, \rho_{n,k} \,] \quad \text{with } 0 \le \rho_{i,k} \le 1$$

The estimated parameter set, ρ_k, defines a set of membership functions, μ_k. The degree of membership of a set x < U to a class C_k is given by the function

$$\mu_k = \prod_{i=1}^{n} \rho_{i,k}^{x_i} (1 - \rho_{i,k})^{(1 - x_i)}$$

The form of the above function is not unique. The function has a maximum value when x_i is equal to $\rho_{i,k}$ as shown in Figure #2. For example, for input data $x_i = 0.7$, the grades of membership functions $u_{i,k}$ are 0.4, 0.3, 0.55, and 0.52 corresponding to $\rho_{i,k}$ equal to 0.2, 0.3, 0.7, and 0.8, respectively. Thus the maximum value is 0.55 when $\rho_{i,k}$ is 0.7, which is equal to x_i. Note the maximum value is not necessarily 1. Each data x_i has equal contribution to the membership function μ_k. The possibility that the value x_i is an object in class C_k depends on the degree of membership of x_i to C_k. The decision for the assignment of elements to classes depends on the values of the maximum membership. That is:

$$C_k = \max_i \mu_i(x) \qquad \text{where } 0<i,\ k<n$$

If the decision disagrees with the training set, the parameter $\rho_k(t)$ will be modified to $\rho_k(t+1)$:

$$\rho_k(t+1) = \rho_k(t) + \frac{1}{N_{k(t)}+1} (\, x(t) - \rho_k(t) \,)$$

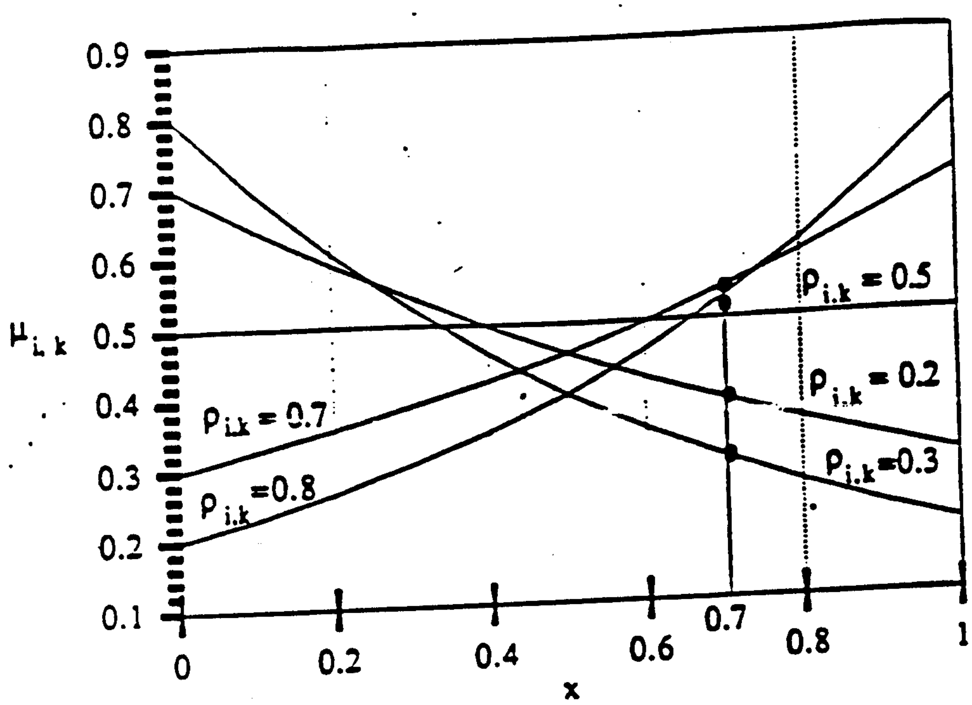

Figure #2: Example membership functions (from Hu, 1991.)

where $N_k(t)$ is the number of training sets assigned to that class at time t. After that, the teaching process will continue until the decision is made correctly according to the given teacher.

For the polygraph there are two classes of data, truth and deceit. As mentioned previously, unlike the statistical approach, the fuzzy classifier can calculate its own membership functions. Also, no preset thresholds are necessary. There may be, however, many membership functions for each class and many descriptors for each membership function. The investigation of this dilemma has been one of the focusses of the project.

C. Proposed Research

1. Hypothesis

Work by the author and his graduate students over the past two years has shown the ability of the fuzzy set algorithm to classify human sleep stages from raw EEG data. Similar to the computer polygraph classification techniques described above, typical computer sleep scoring methods have used parameterization techniques to parse the data before classification. This data separation requires a detailed "Gestalt knowledge" of the behavior of the signal and is prone to being inaccurate over a wide range of subjects. In addition, no concept of the optimality of these parameters is obtained. In order to bypass these problems, the author has used only the EEG time series (raw) data and spectrum applied directly to the fuzzy set. It is theorized that this approach applied to the analysis of the polygraph will also be successful. (See methods section below for a definition of successful classification.)

It is also believed that the transformation of the polygraph data into the frequency domain will allow the fuzzy set to detect such known parameters as baseline shift and amplitude modulation in the respiration rate (suppression and staircase suppression can both be classified as amplitude modulation). For the same reason it is conjectured that the auto- and crosscorrelation of the three different data types will present any correlated behavior of the biological signals to the fuzzy classifier.

In fact, the work proformed under the previous polygraph proposal has begun to confirm these hypotheses (see Appendix A, "Progress Report"). Over 600 features in time and frequency, both individual and cross-correlated, were examined. With little optimization of the fuzzy classification algorithm, classification levels of greater than ninety percent were achieved.

2. Methods

While time-shortened by almost half a year, three out of the five previous project goals were achieved. (Once again, please see Appendix A, "Progress Report" for a complete report.) First, a program for parsing the MGQT data has been developed. This program extracts all waveforms from the the case files and parses the data taking into account the fact that some MGQT questions may be asked out of order, may not always be repeated three times, and may not be asked at all.

Second, a fuzzy classifier has been created, based on the fuzzy k-nearest neighbor algorithm. This algorithm returns a continuous truth versus deception value between zero and one. It was trained on 25 truthful and 25 deceptive files, and achieved 91% accuracy on another set of 25 truthful and 25 deceptive files.

Lastly, relationships between feature sets and classifier success were determined. Of great importance was that the set of four best features had a feature from each one of the physiological channels.

In the proposed study, three goals will be achieved. First, a study of the relationship between fuzzy classifiers and success of classification will be performed. There are several forms of fuzzy classifiers, using both unsupervised and supervised learning. The first phase of this project will focus on which algorithm, or combination of algorithms will be optimal. Specifically, a supervised adaptive fuzzy mebership function algorithm will be compared with the fuzzy k-nearest neighbor algporithm.

Secondly, a comparison between the performance of this algorithm and algorithm used elsewhere is important in understanding its benefits. Therefore, the second phase of this project will focus on comparing our results on the MGQT with our results on the more common zone comparison test.

Finally, the ultimate goal of this project is to create a program that will assist the polygraph examiner in evaluating a subject while the examination is in progress. To do this, the algorithm will output a fracional number from 0 to 1 (0 meaning deceptive and 1 meaning truthful) after each examination question. If the question is a control or irrelevent question, the examiner will tell the program this, and it will learn, in real-time accordingly. Because the examiner is given a continuous measure of truth or deception, he/she can now focus on questions that are yielding indeterminate results.

D. Deliverable

At completion of this project, a highly optimized, real-time, automatic polygraph algorithm will be delivered on IBM PC compatable discs. This program will run on a 80486 PC or faster with at least 4MB of memory. In addition, as was done on the previous project, a complete report will be written documenting all results and operations of the algorithm.

III. Bibliography

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8) Jung Hu and Benjamin Knapp, "Electroencephalogram pattern recognition using fuzzy logic," *IEEE Proceedings of the 25th Asilomar Conference on Signals, Systems, and Computers,* vol. 2, pp. 805-807, November 1991.

IV. Biographical Sketch

Dr. Knapp is an Associate Professor of Electrical Engineering. He received his B.S. from North Carolina State University in 1984 and his M.S. in 1986 and Ph.D. in 1989 from Stanford University, all in Electrical Engineering. While at Stanford he was the recipient of the Hewlett-Packard Faculty Development Fellowship. Dr. Knapp has over 20 presentations and publications in the areas of biomedical signal analysis and man-machine interfaces. He also has 2 patents and 2 patents pending. His work has been described in such places as *Newsweek Magazine* and *Science News*. In addition to running a research laboratory at San Jose State University, Dr. Knapp is a visiting scholar at Stanford University's Center for Computer Research in Music and Acoustics.

V. Budget

One Year Budget Summary
January 1, 1994 - December 31, 1994

	AMOUNT REQUESTED
PERSONNEL	
Salaries:	
Principal Investigator:	
Ben Knapp - 20% Release Time AY	$10,214
Graduate Student Assistants (1):	
6 mos. @ 50% @ $8.50/hr	$4,386
3 mos. @ 100% @ $8.50/hr	$4,386
Total Salaries	$18,986
Fringe Benefits:	
Students @ 5%	$439
Release Time @ 34%	$3,473
Total Fringe Benefits	$3,911
TOTAL PERSONNEL	$22,898
EQUIPMENT	$0
SUPPLIES	$1,000
TOTAL DIRECT COSTS	$23,898
INDIRECT COSTS @ 49% MTDC	$11,710
TOTAL PROJECT COSTS	**$35,608**

Appendix A
Progress Report

1. Overview

A. Development of Data Parsing Algorithm
The first phase of this project was to be able to read the MGQT data files received from the NSA and separate this data into appropriate features for classification. After consulting with the University of Washington, we were able to develop our own data reading program.

After consultation with experienced polygraph examiners and a detailed review of the polygraph literature, the data reading program was then modified to parse the data into a matrix of features. The feature set included, as outlined in the project proposal, time domain, frequency domain, and correlation domain data. Some examples of the feature set are:

Time Domain Features

- Mean, curvelength, area, and standard deviation for all polygraph channels
- Average of the amplitudes of the peaks in the cardio and respiratory channels
- Derivative of the amplitudes of the peaks of cardio and respiratory channels
- Number of peaks in the cardio and respiratory channels
- Inhalation amplitude/exhalation amplitude of respiratory channels

Frequency Domain Features

-Fundamental frequency of cardio and respiratory signals
-Coherancy and cross power spectral density between cardio and respiratory channels
-Power spectral density of cardio and respiratory channels
-Integrated power spectral density for cardio channel

Correlation Domain Features

- Autoregressive parameters (10) for cardio signal
- Cross-correlation between cardio and respiratory channels

B. Design of Fuzzy Classifier Algorithm
Fuzzy classifier design has focused on the development of a fuzzy set based *k nearest neighbor* algorithm. The algorithm learns using a set of MGQT data divided equally between truthful and deceptive. Since there were 150 deceptive files and only 50 truthful files, the deceptive files were divided into three sets of 50 files each. The algorithm was trained separately for each data set. When a question was asked more than once by an examiner the questions were

scored individually and then combined at the end on a majority basis. Some examples of the results achieved using the best four features and no indecision allowed are:

Deceptive Set	%Correct Deceptive	%Correct Truthful	%Correct Total
1	94	78	86
2	89	72	80
3	100	83	91

The following are three reports which describe in detail the work performed. In addition, a copy of a paper which has been submitted to the IEEE International Conference on Fuzzy Systems is also included. Finally, a manual is included which instructs the user how to repeat the work performed at SJSU.

A Comparison of Fuzzy Logic Algorithms for Pattern Recognition

Shahab Layeghi
Electrical Engineering Department
San Jose State University
Professor: Ben Knapp

December 1993

I. Introduction

A great amount of work has been done on the application of fuzzy logic techniques for pattern recognition. In this study some of the more important algorithms are summarized and compared.

Pattern recognition could be defined as search for structure in data. This means organizing data in groups in a way that members of each group have some kind of similarity. A system that does this job is called a classifier. A classifier can be designed by a human expert and be used to classify the data (fixed design). Another approach is to provide the classifier with the data and make it adapt itself according to the data that it receives. Adaptive systems can be divided into two main categories, supervised and unsupervised.

In supervised learning, another system (or a human expert) which is usually called a teacher, furnishes the classifier with the group that each data item belongs to, so that classifier can learn from a set of labeled input data and be able to classify new data. This process is called training.

In unsupervised learning, which is also called clustering, the system is given a set of unlabled data, and it is expected that it find internal similarities between the data items and put them in different groups accordingly. If data are represented quantitatively as vectors in a vector space, data that are spatially close should be put in one group.

In the section ,a method of classification is described which uses fuzzy linguistic variables. This method uses human experts to train the system and then uses the labeled linguistic samples to refine the classifier. In section 2, C-Means Algorithm which is a clustering method is explained. Section 3 covers K Nearest Neighbor algorithm which is a supervised classification method.

After polygraph files were decoded and put in a directory, they could be processed using Matlab. It was tried to write the programs in a structured way so that creating and debugging of individual sections would be easier and program segments would have direct conformity with conceptual block diagrams. At the lowest levels, there are many Matlab routines that operate on pieces of data and extract features from them, and return these features to the calling routines. At the top, there is a Matlab program that extracts the features for all the files in a directory and saves it as a matrix. The structure of these programs is explained in the following sections.

The main feature extraction program is a Matlab routine called **newfeat**. This program finds the features for the files in a directory and saves the features in a matrix. The main part of the program is a loop that extracts the features of a single file and puts them in a vector. This action is repeated for all the files that their name is given. In order for the Matlab program to find the files to processed in a directory, a C program was written that searches in a directory and saves all the names of all the files that it finds in an ASCII file containing a Matlab matrix. This C program is called **'flist'** and could be found in the \polygrap\project\source directory. The way this program works is explained below:

/* This program lists the files in a dos directory and saves this
listing in a file called **files.m**. This file is actually a Matlab script
that contains a matrix called **'flist'** which holds a filename in each row.
The first character of file names can be given to this program as an
input argument.

Ex:

```
        flist t
is equal to use the dos command
        dir t*.*
and save the result in a Matlab m file called files.m


*/
```

After running the flist.exe program in a directory, and checking that the appropriate filenames are saved in the files.m file, the Matlab program can use them by executing the command
files
and using the variable flist.

Another important data item that is used in the feature extraction programs is called **feature_list.** It is a Matlab matrix that includes the names of feature extraction routines. In each row of the feature_list matrix a feature extraction routine is named along with the channel number(s) that this routine will be applied to. For example

'10mean(frag)'

means to apply the mean function to a piece of data called frag, which is defined later. The channel that data is to be gathered from is channel 1. As another example

'26crosscor(frag, frag3)'

means to apply the function crosscor to two pieces of data coming from channels 2 and 6, in variables called frag and frag3.

feature_list is defined in **newfeat** program. All the features that are extracted from the data are listed in it. If a new feature is to be investigated, it is enough to write a program that extracts it, and add that program name in this list.
Note: It is highly recommended that the programs newfeat, feature, and processf be read carefully before making any changes in feature list.

Before being able to do any processing on the data, for each data file another file should be created that holds the types of the questions. These files are named ***zzname*.0x4**. Note that these files are not a standard part of axciton files and were created here by referring to the question files and data sheets that accompanied each the files. The format of these files is as follows:

```
x   0   0   0   0
a1  b1  c1  d1  e1
a2  b2  c2  d2  e2
a3  b3  c3  d3  e3
```

x is either one or zero. 1 means the file is deceptive, and zero means it is non-deceptive. The rows 2, 3 and 4 in this file show the numbers of relevant, irrelevant, and control questions. For example for a deceptive file in which questions 3, 5, 8 and 9 are relevant, questions 1, 2, 4, and 7 are irrelevant, and questions 6 and 10 are control, a question file is constructed that looks like this:

```
1  0  0  0  0
3  5  8  9  0
1  2  4  7  0
6 10  0  0  0
```

The **newfeat** program, for each data file which is listed in flist, loads the above mentioned question file to find the question types. Then it calls the actual feature extraction routine which is called **feature.** The program feature finds all the features for each relevant, irrelevant, and control question and returns the results in a vector. This vector is added as a new column to a matrix called M. At the end of the newfeat program the matrix M is saved in a file. This file is manipulated by another program called **processf**.

processf is a program that loads the M matrix, combines the features for each question in different ways that are explained in reports of Mitra and Shahab, and saves the resultant matirx, the F matrix, in a file.
The above procedure was repeated for the polygraph files in several directories. One of the directories contained files for non-deceptive cases and the other ones included deceptive files. Three sets of data were built by combining the features for non-deceptive cases with three sets of deceptive files. Each data set contained 50 deceptive and 50 non-deceptive cases. These sets were used by classification programs.

Classification:

There are two classifier programs written for this project, fknn and cknn, which implement fuzzy and crisp K-nearest neighbor classifiers accordingly. These programs are written in C programming language. The way they interact with Matlab is through reading and writing files in Matlab format, that is **.mat** files. There are two C functions inside these programs called loadmat and savemat which are interfaces to Matlab files and can be used to load and save date, which in Matlab are matrices, from Matlab files. These two functions are in a file called **matldsv.c** which should be compiled with the source files that use them. fknn and cknn programs load matrices that include the features and were prepared by Matlab feature extraction routines. After loading the matrices, the feature vectors in test matrix are classified individually, and the result is saved in a file as a Matlab matrix. The comments in the source codes of the programs cknn and fknn are repeated here for reference:

/* **cknn**: This program implements a K-nearest neighbor classifier.

The main program opens a Matlab data file, reads the training matrix, classifies each entry in the testing matrix, and writes the result in an output file. The file that this program gets the information from should be called "cdatafil.mat". As the name implies it is in Matlab file format. The data in this file should have the following order:

1. A single variable 'C' which is the number of classes.
2. A single variable 'K' which is the parameter 'K' in K-NN Algorithm.
3. A training matrix 'P' which contains a set of feature vectors. Each vector is in a column of the matrix.
4. A classes vector 'T' which contains the classes of the training set
5. An input matrix 'U' which contains a set of unclassified feature vectors.

The main program uses the Crisp KNN routine to classify each one of the input vectors and saves the results (the classes that these inputs belong to) in a file called coutfile.mat. This file is in Matlab format. This file contains a vector of the classes called:

'cresult'

This program can be called from dos, or within Matlab by using dos escape character '!'. An example Matlab script file that shows how this program can be used is included in the file "cknntest.m".

*/

/* **fknn**: This program implements a fuzzy version of K-nearest neighbor classifier.

The main program opens a Matlab data file, reads the training matrix, classifies each entry in the testing matrix, and writes the result in an output file. The file that this program gets the information from should be called "fdatafile.mat". As the name implies it is in Matlab file format. The data in this file should have the following order:

1. A single variable 'C' which is the number of classes.
2. A single variable 'K' which is the parameter 'K' in K-NN Algorithm.
3. A single variable 'M' which is the coefficient in fuzzy algorithm.
4. A training matrix 'P' which contains a set of feature vectors. Each vector is in a column of the matrix.
5. A class membership matrix 'T' which contains the membership values of the training set vectors to the classes.
6. An input matrix 'U' which contains a set of unclassified feature vectors.

The main program uses the Fuzzy KNN routine to classify each one of the input vectors and saves the results (the memberships of the inputs to classes) in a file called "foutfile.mat". This file is in Matlab format. This file contains a single variable called fresult. It is a matrix of the memberships of the inputs to the classes.

This program can be called from dos, or within Matlab by using dos escape character '!'. An example Matlab script file that shows how this program can be used is included in the file "fknntest.m".

*/

As mentioned above, the programs fknn and cknn are the actual classifiers which can be called directly from dos or within a Matlab program. Several Matlab programs were written that used these two programs for classification of data. The Matlab programs acted mostly as a front end or user interface for the classifier programs. A listing of many Matlab programs and functions is included as an appendix in this report. Understanding of all the functions is not necessary because they are used inside the programs. Some of the programs were created to test other programs or to experiment with the data. These programs are not necessary for classification, but knowing about them might help to prevent recoding routines that are already there. In the case of user interface programs, the best way is to run them and become familiar with the way they work. They were intended to be very flexible, and usually by changing a few parameters inside the code, they can be used for other purposes.

Classifier programs were used not only to classify a given data set, but also to select a set of good features from all the features that initially were tried. For a detailed discussion of the steps involved in this refer to Shahab's and Mitra's reports. Some of the programs and data files which were used or produced in this stage are explained here:

Classify is a Matlab program that loads a feature matrix from a .mat file, randomly breaks it into a set of training, and a set of testing feature vectors, classifies every entry in the testing set using all the entries in the training set by calling either fknn or cknn programs, repeats this process a number of time, and returns the result of classification of each file and the percentage of correct classification and a performance index for the classification. Some of the parameters like the filename to load can be changed inside the program classify.m. Other parameters can be changed while the program is running. This program is extremely useful for experimenting with combinations of features, and even includes an option to plot the scattering of the first two features.
Note: By setting percent_training=1, The testing and training sets wont be randomly selected, instead, all the entries except one are used in the training set and that entry is classified. This action is repeated for all the entries in the matrix.

Clas_aut is an automated version of classify program. Instead of asking the user for entering parameters, this program includes a loop that checks the classifications using all the features individually. The results are saved in a file called **clas_res**. All the other parameters should be set in the program. It should be noted that running this program might take a long time depending on the number of features and repetitions. **Clasaut2**, **clasaut3**, and **clasaut4** are alterations of clas_aut that instead of using single features use combinations of 2 to 4 features. Clasaut2 tries all the pairwise combinations of the features. Clasaut3 and clasaut4 use the combinations of 2 and 3 features supplied to them in the program and combine them with other features to test the combinations of 3 and 4 features.

bestfk is a Matlab script that sorts the features according to their performance in classifying the files. Note that the correct_classification vectors for data sets 1-3 were saved as res1, res2, and res3 in a file called **Knn-res**. This file is loaded by the bestfk program. The best features are found for the three data sets. For more details about the selection strategy refer to Shahab's report. It is informative to look at the program code to find out about the outputs that it produces.
Bestfs is the same program as bestfk. The only difference is that it loads the results from a file called **scat_res**. This file is produced by saving the results of the scatter criterion.

Scat is a Matlab function that finds the scatter criterion for the feature vectors in a matrix. It was used for the feature matrices of sets 1-3, and the results were saved in scat_res. **Bestf2**, **bestf3**, and **bestf4** work the same way as bestfk, but as output give the best combinations of 2-4 features.

Appendix: A listing of the Matlab programs

bestf2:
This Matlab script finds the best 30 combinations of features from three sets of features. Same features are tried on 3 sets of data.
This is used to rank the combinations of 2 features

---

bestf3:
Same as bestf2, but for combinations of 3 features.

---

bestf4:
Same as bestf2, but for combinations of 4 features.

---

bestfs:
This Matlab script tries a method to find the best 30 features from three sets of features. Same features are tried on 3 sets of data. Scatter criterion is used to measure each feature's performance.
Note that for the features 1-651 each set of seven features are in fact the same feature combined differently for different features. For the rest of the features i.e. 652-669 each set of three is the same feature.

---

bestfk:
This Matlab script tries a method to find the best 30 features from three sets of features. Same features are tried on 3 sets of data. The results of classification using a KNN classifier is saved on a vector called correct_res.
Note that for the features 1-651 each set of seven features are in fact the same feature combined differently for different features. For the rest of the features i.e. 652-669 each set of three is the same feature.

---

clas_aut
This program adds a loop to the classify program. It repeats classification for different input vectors. It saves the results (percentage correctly classified and performance index)
as two vectors in a file called clas_res.

---

clasaut2:
This program adds a loop to the classify program. It repeats classification for different combinations of 2 features. It saves the results (percentage correctly classified and performance index) and the indexes of these features in a file called clasres2.

---

clasaut3:
same as clasaut2, but for the combinations of 3 features.

---

clasaut4:
same as clasaut4, but for the combinations of 4 features.

---

classify:

This script parses a matrix of polygraph
vectors into training and testing vectors.
It then calls the classifier, trains, tests
and gives results.

---

cluster1:
This is a program that tests the K-Nearest-Neighbor
algorithm with a set of two class data that have
gaussian distribution

---

cluster2:
Another program like cluster1.

---

feattst:
An older version of classify.

---

feattst2:
Another version of feattst.

---

featurev:
Mitra

---

plotf:
This script prompts the use to enter two features and plots them.

---

randvect:
function [y,x] = randvect(elements,maximum)

This function creates a vector
of random numbers between 1
and the maximum number given
to the function (maximum).
The length of the vector is
specified by the number of
elements given to the function.
e.g. randvect(elements,maximum)

---

scat:
function J=scat(Sample, Class)

J=scat(Sample, Class)
returns a value that shows how the labeled samples of a two class distribution are scattered. Samples is a vector that contains the values of the samples. Class is a vector that contains the class labels(0 or 1).
The criterion function is:

J=(m1-m2)^2 / s1^2+s2^2
m's are the means for the classes and S's are scatters of samples.
Larger result means better separation between the classes.
Reference: Pattern Classification and Scene Analysis, Duda and Hart

---

scatv

function JV=scatv(M, Class)
scatv returns a vector that contains the scatter criterion of a matrix.
each row of the matrix M contains values of the samples for one feature.
Class is the class labels for the samples.
see also scat

Appendix D: Use of Fuzzy Set Classification for Pattern Recognition of the Polygraph

Ramin Djamschidi

Fall 1994

Use of

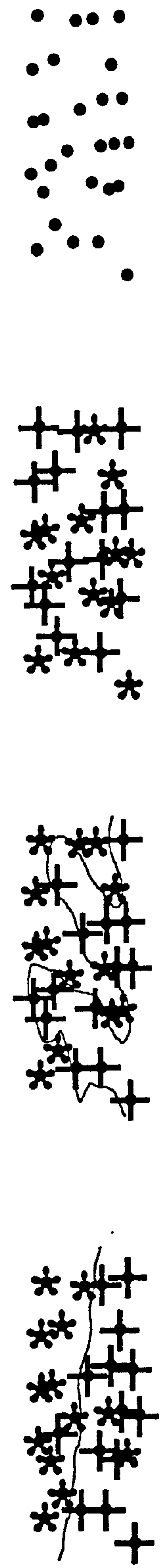
FUZZY

Set Classification for

PATTERN RECOGNITION

Of the

POLYGRAPH



A Thesis
Presented to
The Faculty of the Department of Electrical Engineering at

San Jose State University
and
Rheinisch-Westfälische Technische Hochschule Aachen

In Partial Fulfillment
of the Requirements for the Degree
Diplom

By
Ramin Djamschidi
San Jose, California
September, 1994

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Lehrstuhl für Biomedizinische Technik

der Rheinisch-Westfälischen Technischen Hochschule Aachen

Univ.-Prof. Dipl.-Ing. Dr. rer. nat. Günter Rau

Helmholtz-Institut · Pauwelsstraße 20 · D-52074 Aachen
Telefon: (0241) 80-7111/12 · Telefax: (0241) 8888-418

D I P L O M A R B E I T

für

Herrn Ramin Djamschidi

"Use of fuzzy set classification for pattern recognition of the polygraph"

23. März 1994

....
Univ.-Prof. Dr. rer. nat. G. Rau

....
Vorsitzender des Prüfungsausschusses

D I P L O M A R B E I T

für

Herrn Ramin Djamschidi

<u>Theme</u>: Use of fuzzy set classification for pattern recognition of the Polygraph

<u>Task description</u>:

Polygraph testing has been used as a technique for measuring deception throughout the twentieth century. Throughout most of this time period the task of interpreting the data has rested solely on the trained examiner. Recently, automated computer evaluation of the polygraph using statistically derived discrimination functions has begun in an effort to aid the polygraph examiner. The purpose of this diploma thesis is to investigate the use of fuzzy set classification to perform the data analysis. The capability of the fuzzy membership functions to be trained relatively quickly will enable computer evaluation of the polygraph to adapt to individual subject differences, possibly during the testing procedure. This training may also reveal important parameters of the polygraph data which have not yet been considered useful.

The diploma thesis will have three parts. The first will be in determining an optimal fuzzy pattern recognition technique for polygraph analysis. While previous students have investigated an optimal feature set, an optimal classifier has yet to be determined. Secondly he will test this optimal classifier on two types of polygraph data. Finally he will work on getting this algorithm to operate in a psuedo-real-time environment based on an 80486 personal computer.

Beginn der Arbeit: 31.3.1994
Tag der Abgabe: 30.9.1994

Betreuer: Dr. B. Knapp
Associate Professor
Dep. of Electrical Engineering
San Jose State University

Berichter: Univ.-Prof. Dr. rer. nat. G. Rau

Ich versichere, daß ich diese Arbeit im Rahmen der Betreuung durch die Institute selbständig angefertigt habe.

Aachen, den 30.09.1994

(Unterschrift)

Die Arbeit ist nur zum internen Gebrauch bestimmt.

Table of contents

§1. ABSTRACT

Polygraph tests are a widely used method to distinguish between truth and deception. During a polygraph test, the subject is asked a series of control, relevant and irrelevant questions which provide different physiological responses useful for a comparison. The three physiological responses that are currently measured are Electrocardiogram, Galvanic Skin Response (GSR) and Respiration.

Polygraph charts are usually analyzed by human interpreters. However, computer algorithms are now being developed to score the tests or verify the results. These methods are based on *statistical* classification techniques.

In this study two different *fuzzy* algorithms were implemented to classify the polygraph charts, using a number of time, frequency and correlation domain features. These two algorithms and their results were then compared with those from the previous works. The major advantage of using fuzzy set theory is that it does not simply assign each input to one of the clusters, but it gives a degree of belonging of an input to each cluster.

The average correct detection rate we achieved in this study was 80% - 85%. Using certain set of data we even obtained up to 97% correct detections.

§2. INTRODUCTION

2.1. POLYGRAPH[1]

2.1.1. Preview:

Polygraph examinations are the most widely used method to distinguish between truth and deception. In a Polygraph examination a person is connected to a special instrument called a Polygraph which records several physiological signals such as blood pressure, Galvanic Skin Response, and respiration. The subject is asked a set of questions by an examiner. By looking at these signals the examiner is able to determine the reactions of the subject to the questions and decide whether the person was truthful or deceptive in answering each question.

The problem with human classification of Polygraph tests is that the outcome depends on the examiner's experience and personal opinion. Automatic scoring of Polygraph tests has been a subject of extensive research. Several methods for Polygraph classification have been studied which are mostly based on *statistical* classification techniques.

Digitized Polygraph data used in this project were collected from various police stations. The data files were organized according to the test format used and were decoded to ASCII format so they can be read by Matlab. Preprocessing and feature extraction routines were implemented in the Matlab language in privious works [Layeghi1993,1] [Dastmalchi1993][Jacobs1993]. Three sets of files were chosen, each one of them contained 50 deceptive and 50 non-deceptive files.
These files are listed in the appendix, Fig.42.

2.1.2. History:

The first attempt to use a scientific instrument in an effort to detect deception occurred around 1895 [Reid1966]. That was the year that Caesar Lombroso published the results of his experiments in which a hydrosphygmograph was used to measure the blood pressure-pulse changes of criminals in order to determine whether or not they were deceptive. Although the hydrosphygmograph was originally intended to be used for medical

[1]Portions of this section were extracted from [Layeghi1993,1] using particularly [Capps1992] [Olsen1983] [Reid1966].

purposes, Lombroso found that it worked well for lie detection. Lombroso may have been the first to use a peak of tension test format. This was done by showing a suspect a series of photographs of children, one being the victim of sexual assault. If the suspect did not react more to the victims picture than the pictures of the other children, Lombroso concluded that the suspect did not know what the victim looked like and therefore was not the alleged perpetrator.

In 1914 Vittorio Benussi published his research on predicting deception by measuring recorded respiration tracings [Capps1992]. He found that if the length of inspiration were divide by the length of expiration, the ratio would be larger after lying than before lying and also before telling the truth than after telling the truth. In 1921 John A. Larson constructed an instrument capable of simultaneously recording blood pressure pulse and respiration during an examination [Reid1966] [Capps1992]. Larson reported accurate results which prompted Leonarde Keeler to construct a better version of this instrument in 1926 [Reid1966] [Capps1992].

The use of galvanic skin response in lie detection began during the turn of the century. It's usefulness, however, did not become evident until the 1930's during which time several articles written by Father Walter G. Summers of Fordham University in New York [Capps1992]. In these articles he reports over 90 criminal cases in which examination using the galvanic skin response had all been successful and confirmed by confession or supplementary evidence.

The usefulness of the galvanic skin response prompted Keeler to add an galvanometer to his polygraph. At the time of Keelers death in 1949, the Keeler Polygraph recorded blood pressure-pulse, respiration, and galvanic skin response [Reid1966].

2.1.3. Modern Test Formats:

The effectiveness of a polygraph examination is often the result of the test format that is used. A polygraph test format consists of an ordered combination of relevant questions about an issue, control questions that provide a physical response for comparison, and irrelevant questions that also provide a response or the lack of a response for comparison [Olsen1983][Capps1992].

Three general types of test formats are in use today. These are *Control Question Tests*, *Relevant-Irrelevant Tests*, and *Concealed Knowledge Tests*. Each of the general test formats may have a number of more specific variations. Each examination consists of two to five sessions containing a prescribed series of questions. The test format that is used in an examination is determined by the test objective [Reid1966] [Capps1992].

1. The *Concealed Knowledge Test*, also called peak of tension test, is used when facts about a crime are known only by the investigators and not by the public. In this case, a subject would not know the facts unless he or she was guilty of the crime. For example, if a gun was used in a crime and the public did not know the caliber, an examiner could ask a suspect, if it was a 22 caliber, a 38 caliber, or a 9 mm. If the gun used was a 9 mm and the suspect was deceptive, a polygraph chart would probably indicate evidence of deception.

2. A *Control Question Test*[2] is often used in criminal investigations. In this type of test a series of relevant, irrelevant, and control questions are asked:

- A relevant question is one which is specific to the crime being investigated. For example, "Did you steal the money?".

- A control question is designed to make the subject feel uncomfortable. It is not specific to the crime being investigated however it may be related in an indirect way. A control question that could follow the relevant question stated above is "Have you ever taken anything that did not belong to you?". The control questions are compared to the relevant questions and if the responses to the relevant questions are greater, the subject is usually classified as deceptive.

- Irrelevant questions are used as buffers. Examples of irrelevant questions are "Are the lights in this room on?" or "Is today Monday?".

3. *Relevant-Irrelevant Tests* are usually used to test people trying to obtain security clearance or get a job. In this test, relevant questions are compared to irrelevant questions. Very few control questions are asked. The purpose of control questions in this test is to make sure that the subject is capable of reacting at all.

---

[2] It was decided to use this method in our project (as it was also in previous works).

2.1.4. Present Day Equipment

The most popular polygraph machines today are the Reid Polygraph developed in 1945 and the Axciton Systems computerized polygraph developed in 1989 [Olsen1983]. The Reid polygraph scrolls a piece of paper under pens that record the biological signals. The Axciton polygraph digitizes physiological signals and uses a computer to process them. The sampling frequency of the Axciton machine is 30 Hz. Axciton provides a computer based system for ranking the subject responses but allows printouts of the charts to be scored by hand the traditional way.

Both machines record the same biological signals using standard methods. Blood pressure is measured by placing a standard blood pressure cuff on the arm over the brachial artery. Respiration is monitored by placing rubber tubes around the abdominal area and the chest of the subject. This results in two signals, a lower and upper respiratory signal. Skin conductivity is measured by placing electrodes on two fingers of the same hand.

The focus of this thesis is to investigate two different fuzzy pattern recognition algorithms using the aforementioned signals.

2.2. PATTERN RECOGNITION UTILIZING FUZZY TOOLS

2.2.1. Why the "FUZZY" approach?

While observing the history of science, we notice that one of its major goals has always been what we call today "pattern recognition". Having this in mind, man created models, functional relationships and mathematical tools to come closer to a perfect and precise model for almost every area of the nature and our being. In fact, *"precision"* became more and more important, to the extent that an *imprecise* model was a *bad* model by default.

1965 Lotfi A. Zadeh introduced in his innovative paper [Zadeh1965] an *"imprecise"* structure for mathematical observation; Hence, the *fuzzy set* was born. A companion to the classical one with often more useful and suitable representation of our environment.

"The fuzzy set was conceived as a result of an attempt to come to grips with the problem of pattern recognition in the context of imprecisely defined categories. In such cases, the belonging of an object to a class is a matter of degree, as is the question of whether or not a group of objects form a cluster"; These were the introductory words from L.A. Zadeh in [Bezdek1981]. They summarize the fundament of any fuzzy clustering or classifying algorithm concerning any search of data structure or pattern recognition. This concept is exactly what this project is all about.

An example:

Imagine, you have two groups of objects "chairs" and "desks" in different varieties. In a simple version of a typical pattern recognition problem, you have the task to cluster or classify the given objects into these two groups. In reality, we will also have other objects like a big box or a bed within the pool of the objects, but only the two aforementioned clusters by definition. Now, a conventional crisp clustering method would put these critical objects in either one of these two clusters. Thus, the big box or the bed may be labeled as if they would be chairs.

A fuzzy clustering method would label the objects with *soft* membership values. In this case, a big box (that can be used as a chair or a desk) might be labeled with 0.6 degree chair and 0.4 desk. Information like this serves a useful purpose - "fuzzy memberships in several classes are a signal to take a second look" [Bezdek1993] [Bezdek1992]:

Hard memberships of data cannot support this. Thus, the fuzzy model provides a richer and more flexible solution structure, one that models the real objects with a finer degree of detail than the harshness of the crisp models. Notice also that hard membership values build a subset of the fuzzy membership[3] set.

There are different types of fuzzy algorithms to find the appropriate membership values within the data. In this project, we used the follwoing two approaches:

1. Clustering algorithms:

Given any finite data, the problem of clustering is to find similarities between the objects of the data and to assign labels that matching objects would belong to the same subgroups. The algorithm starts its search without any initial interpretative information about the data elements. It *only* seeks for objective numerical similarities between the elements. Because the initial objects are unlabeled, this method is often called "unsupervised learning". The word *learning*[4] implies that the clustering algorithm will ultimately find the correct labels at the end of the process. This is what we hope to obtain, but we do not know it a priori.

Notice that because of the unsupervised nature of this algorithm, we may find "correct" clusters which represent some similarities, but not the ones we were looking for. In the aforementioned example with chairs and desks, the algorithm may provide two clusters of "wood-made" and "metal-made" objects (which are also correct), but not "chairs" and "desks" as we had hoped for.

In this case, the performance of a clustering model is influenced by the choice of the parameters[5], features, geometrical properties and our eventual interpretation of the labels.

2. Classifying algorithms:

In contrast to a clustering system which labels a given data, a classifier is capable - once it is defined (and trained) - of labelling every appropriate data. In addition, a classifying system is *ususally* initialized by labeled objects. In these cases, we call this method "supervised learning".

[3]Notice that membership values are *not* probabilities; they are similarities of object vectors to a class structure. They represent the degree of belonging of an object to a group of objects.
[4]The word *learning* does not imply any *training*. In fact, a clustering system - as is its nature - is almost the opposite of any system which *learns* by *training*.
[5]See chapter 2.2.3.2. for the meanings of the parameters and chapter 3.1.3.3. for the strategies we used.

Notice that we can also use a clustering algorithm as a modified classifying algorithm: After having set the optimal combination of parameters and features, we can use the clustering system to classify any new data by:

- adding the new element to a given and already correct clustered data, and letting the system *re*label[6] the data. Thus, our new object ends up to be in one of the clusters representing its identity,

- saving all the parameters, cluster centers and the data elements and calculate appropriately the membership value of the new object, which will eventually represent its identity.

[6]Running a new clustering process with one more element will probably change the structure of the original clusters, because the cluster centers and the membership values of each element depend on *all* of the members. In spite of this fact, we will be able to classify a normal (= not an outlier) object by having a large number of already clustered objects in a stable condition.

2.2.2. Why fuzzy-c-means (FCM)?

One of the most significant characteristic of *fuzzy*-c-means algotithm is its "fuzziness"[7], as the name assumes. Unlike crisp clustering methods, FCM gives us "membership functions" $\subset [0, 1]$ which determine the *grade* of belongingness of the elements to a cluster. As mentioned before, this information is totally lost by conventional clustering techniques. The advantage of FCM is the fact that the results we may get from a crisp clustering method are automatically within those from FCM.

We chose FCM as an alternative and a comparison to the fuzzy K-Nearest-Neighbor algorithm (KNN) investigated previously [Layeghi1993,1][Dastmalchi1993][Jacobs1993], specially because FCM is an *unsupervised* clustering method which works only by using "mathematical" tools such as spatial distances or similarities, without any training or additional interpretative information.

By this method, good[8] features will then hopefully provide an optimal mathematical grouping that presents in some sense an accurate portrayal of natural structures in the physical process from where the polygraph data are drived.

Why we chose FCM algorithm:

Because it

- **does not need previous training,**
- **does not make any assumption about the distribution of samples,**
- **is unsupervised, objective and self organized,**
- **can be used as an alternative and a comparison to fuzzy KNN investigated previously.**

Fig.1: FCM characteristics

[7]See chapter 2.1.1. for characteristics of a fuzzy approach.

[8]"Good" features are in our study those which can cluster the data in deceptive and truthful groups.

2.2.3. Fuzzy-c-means algorithm and its interpretation

2.2.3.1. FCM code - An iterative procedure:

The fuzzy-c-means algorithm[9] is basically an iterative procedure to minimize an objective function J_m representing a spatial fuzzy distance between data points x_k and cluster centers v_i. In this project, I chose the most widely used Euclidean distance, i.e. the sum of the squared errors performance index;

$$J_m(U,v) = \sum_{k=1}^{n} \sum_{i=1}^{c} (u_{ik})^m \left\| x_k - v_i \right\|_A^2$$

- $X = \{x_1, x_2, \ldots, x_n\} \subset \Re^s$ is a finite data set in the pattern space $\Re^s$.
- c is a fixed and known number of clusters (here: c=2).
- $U = [u_{ik}] \in \Re^{cn}$ is a fuzzy c-partition of X, u_{ik} is referred to as the grade of membership of x_k to the cluster i. u_{ik} satisfy the following constraints;

$$u_{ik} \in [0,1]; 1 \le i \le c, 1 \le k \le n$$

$$\sum_{i=1}^{c} u_{ik} = 1; 1 \le k \le n$$

$$0 < \sum_{k=1}^{n} u_{ik} < n; 1 \le i \le c$$

- $V = (v_1, v_2, \ldots, v_c) \in \Re^{cs}$; each $v_i \in \Re^s$ represents a prototype of class i.
- m is the weighting exponent and represents the level of fuzziness; $1 \le m < \infty$.

---

[9] [Ruspini1969] was the first one who suggested the structure of *fuzzy-c-partition* spaces. The fuzzy-c-means algorithm (originally ISODATA) was initially developed by [Dunn1974] and generalized by [Bezdek1973].
Dunn extended and developed the classical "within-groups sum of the squared errors" (WGSS) function to a fuzzy clustering criterion and developed the fuzzy-c-means clustering algorithm to minimize the objective function through an iterative method. Bezdek further extended the fuzzy objective function proposed by Dunn to a more genral form of fuzzy clustering criterion by introducing the weighting exponent m, $1 \le m < \infty$. It turns out that Dunn's function is a special case (m=2) of an infinite family of objective functions.

• $\|x_k - v_i\|_A^2$ is an inner product induced norm on $\Re^s$.

By differentiation $J_m(U,v)$ with respect to u_{ik} where v_i is fixed and to v_i where U is fixed, we obtain

$$u_{ik} = \frac{1}{\sum_{j=1}^{c}\left[\frac{\|x_k - v_i\|^2}{\|x_k - v_j\|^2}\right]^{\frac{1}{m-1}}}$$

and

$$v_i = \frac{\sum_{k=1}^{n}(u_{ik})^m x_k}{\sum_{k=1}^{n}(u_{ik})^m}.$$

These two equations cannot be solved analytically, but approximate solutions can be obtained by an iterative procedure. The FCM uses iterative optimization of an objective function based on a weighted similarity measure between data points and cluster centers.

Step 1. Input the number of clusters, c, the weighting exponent, m, and the error tolerance, ε.
Step 2. Input the data X = { $x_1, x_2, \ldots, x_n$ }.
Step 3. Initialize the membership values $U = [u_{ik}]$.
Step 4. Calculate the new cluster centers $V^{(l)}$ by the 3rd equation.
Step 5. Update the $U^{(l)}$ by the 2nd equation.
Step 6. Return to Step 3, if $\left\|U^{(l+1)} - U^{(l)}\right\| > \varepsilon$; otherwise output U...

X: [sxn]	n: # of data elements - polygraph test sessions.
U: [cxn]	s: # of features - dimension of the samples in each cluster.
V: [sxc]	c: # of clusters

Fig.2: The iterative FCM[10] procedure

[10] See Fig.3 , the flow chart of the FCM code implemented in this project.

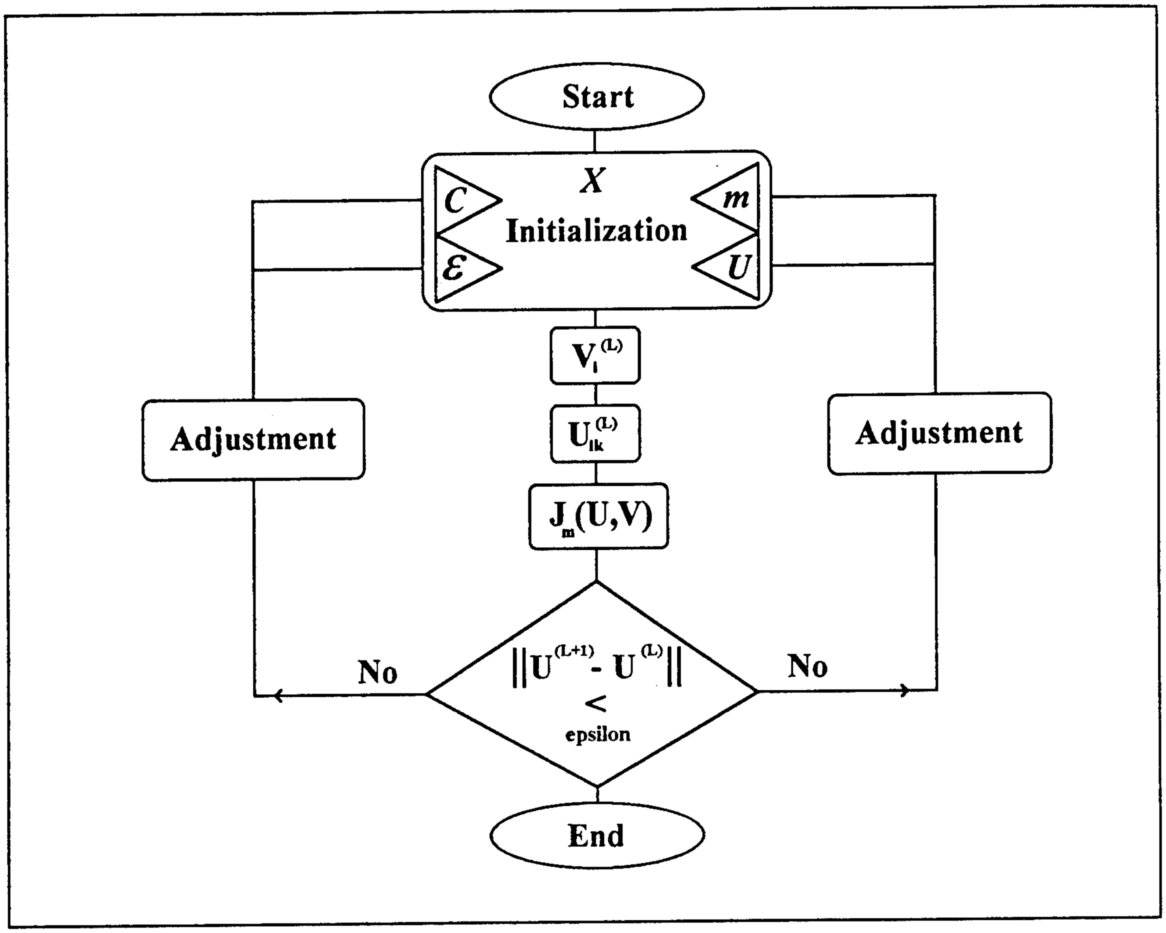


Fig.3: Flow chart of the FCM code implemented in this project

<u>*2.2.3.2. What the influential parameters practically mean or represent, and how to interpret the clustering algorithm itself:*</u>

The weighting exponent m represents the "fuzziness" level. It controls the extent of membership sharing among the fuzzy clusters. Recall the example of the two clusters, "desks" and "chairs" in chapter3.1; In a *hard* c-means clustering environment ($m \to 1$) each object can either belong to "chairs" or "desks", i.e. its membership value is either one or zero for each cluster. Now, the higher m is, the fuzzier the results will be. Thus, a desk - which can also be used as a chair- may get a membership value higher than zero for belongingness to the chairs cluster. In this sense, m controls the membership values as following

$$\lim_{m \to \infty} u_{ik} = \frac{1}{c}.$$

The control parameter epsilon represents the interrupt criterion. It influences the number of iterations and therefore the accuracy of the algorithm which is the search for c minima. By making epsilon smaller we get more accurate clustering results, but also more computing time, which is not important in this specific case.

The algorithm primarily gives us after each iteration new cluster centers V_i and new membership values U_{ik}. It then calculates the spatial distances between each data element and the found cluster centers then checks the interrupt criterion. If these distances are small enough, the algorithm will eventually give us the best membership values and the appropriate cluster centers. At this point, the search for an internal structure within the polygraph data -the original intention of every clustering process- will be finished.

FCM algorithm belongs to the so-called *partitional* clustering algorithms which generate a fuzzy c-patition matrix in a feature space. In this project I set the number of clusters c, as a known parameter, equal to two. It can otherwise be a part of the clustering optimization itself. This decision was made after running some initial tests with $c = 3$ as well, which represents "deceptive", "truthful" and "ambiguous" clusters.

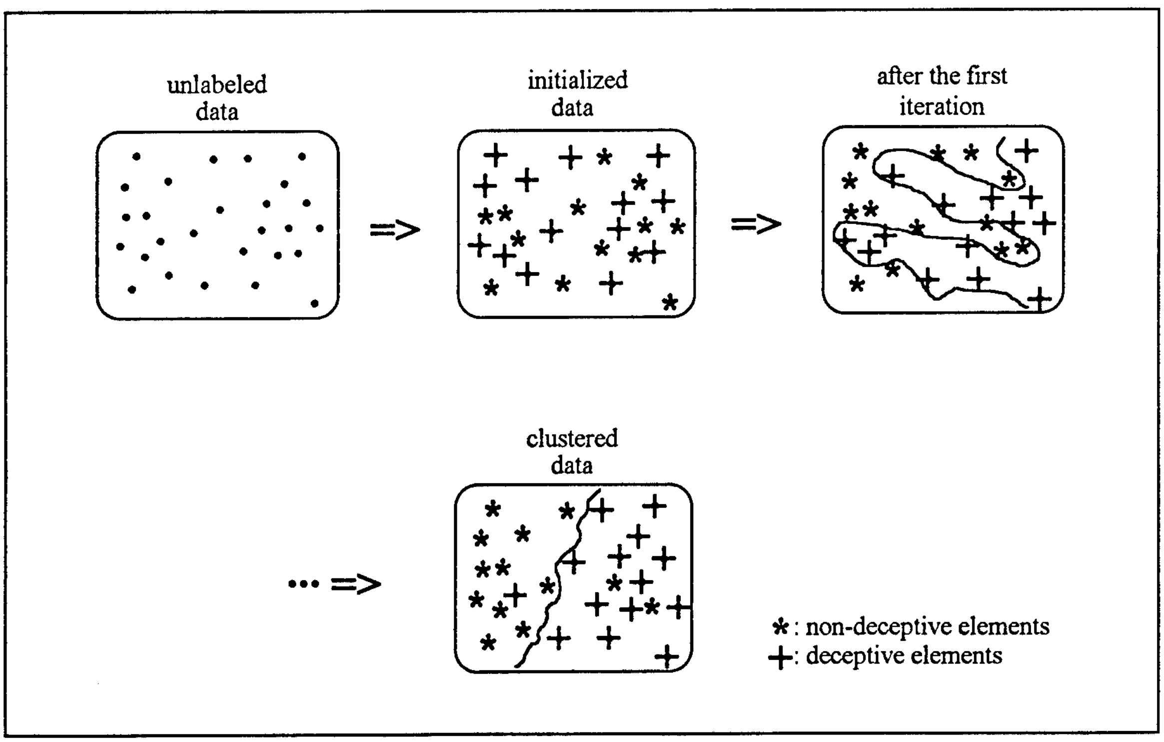


Fig.4: Fuzzy C-means algorithm applied on polygraph data

2.2.4. Why LMS fuzzy adaptive filter?

Filters are information processors. In practice, information[11] usually exists in two different modes:

- Numerical data associated with the problem,
- linguistic descriptions of human experts
  (often in the form of fuzzy IF-THEN rules)

Conventional filters can only process numerical data, whereas expert systems can only make use of linguistic information, i.e. a successful pattern recognition system in conventional form can only be guaranteed where either linguistic rules or numerical data do not play a critical role. Recall the fact that even in those cases we decide for a numerical method, we use linguistic information, consciously or unconsciously, in the choice among different filters, the evaluation of filter performance, the choice of the filter orders, the interpretation of filtering results, and so on.

The LMS[12] fuzzy adaptive filter is a new kind of nonlinear adaptive filter which makes use of both linguistic and numerical information concerning the physical characteristics of the polygraph data in their natural form. This filter is constructed from a set of changeable fuzzy IF-THEN rules, i.e. we have the choice of setting the rules according to our experiences and incorporating them directly into the filter, or initializing the rules arbitrarily; similar to the polynomial, neural nets, or radial basis function adaptive filters.

2.2.5. LMS fuzzy adaptive filter and its interpretation:

2.2.5.1. Filter code - An adaptive procedure

As stated before, this filter is constructed from a set of changeable fuzzy IF-THEN rules by matching input-output pairs through an adaptation procedure. The adaptive algorithm updates the parameters of the membership functions which characterize the fuzzy concepts in the IF-THEN rules by minimizing a criterion function.
Consider a real-valued vector sequence $[\underline{x}(k)]$ and a real valued scalar $[d(k)]$. The adaptive filter $f_k: U \to R$ is to determine, such that $L = E[(d(k) - f_k(\underline{x}(k)))^2]$ is minimized.

---

[11] About the pattern of the subject to be studied.
[12] LMS = Least Mean squares

With $k = 1,2,3,\ldots$ and $\underline{x}(k) \in U \equiv [C_1^-, C_1^+] \times [C_2^-, C_2^+] \times \cdots \times [C_n^-, C_n^+] \subset R^n$. U and R are the input and output spaces of the filter, respectively.

The following steps describe the LMS fuzzy adaptive filter[13] used in this project:

Step 1: M fuzzy sets F_i^l are to be defined in each interval $[C_i^-, C_i^+]$ of U with the following Gaussian membership functions

$$\mu_{F_i^l}(x_i) = \exp\left[-\frac{1}{2}\left(\frac{x_i - \overline{x_i^l}}{\sigma_i^l}\right)^2\right]$$

where $l = 1,2,\ldots,M$, $i = 1,2,\ldots,n$, $x_i \in [C_i^-, C_i^+]$, and $\overline{x_i^l}$ and σ_i^l are free parameters which will be updated in the LMS adaptation procedure of Step 4.

Step 2: A set of M fuzzy IF-THEN rules is to be constructed in the following form:

$$R^l: \text{ IF } x_1 \text{ is } F_1^l \text{ and } \ldots\ x_n \text{ is } F_n^l, \text{ THEN } d \text{ is } G^l,$$

$$\ldots$$

$$R^M: \text{ IF } x_1 \text{ is } F_1^M \text{ and } \ldots\ x_n \text{ is } F_n^M, \text{ THEN } d \text{ is } G^M.$$

where $\underline{x} = (x_1, \ldots, x_n) \in U$, $d \in R$, F_i^l's are defined in Step 1, and G^l's are fuzzy sets defined in R. The (parameters of) membership functions $\mu_{F_i^l}$ and μ_{G^l} in these rules will change during the LMS adaptation procedure of step 4. Therefore, the rules constructed in this step are *initial* rules of the fuzzy adaptive filter.

Step 3: The filter $f_k: U \to R$ is constructed based on the M rules of the Step 2 as follows:

$$f_k(\underline{x}) = \frac{\sum_{l=1}^{M} \theta^l \left(\prod_{i=1}^{n} \mu_{F_i^l}(x_i)\right)}{\sum_{l=1}^{M} \left(\prod_{i=1}^{n} \mu_{F_i^l}(x_i)\right)}$$

where $\mu_{F_i^l}$'s are the Gaussian membership functions of Step 1, and $\theta^l \in R$ is any point at which μ_{G^l} achieves its maximum value.

[13]This algorithm is suggested in [Wang1993] and [Wang1994].

Because we chose the membership functions to be Gaussian functions which are nonzero for any $x_i \in [C_i^-, C_i^+]$, the denominator of the last equation is nonzero for any $\underline{x} \in U$. Therefore, the filter f_k is well defined, and because the θ^l as well as $\overline{x_i^l}$ and σ_i^l are free parameters, this filter is nonlinear in the parameters.

Step 4: The following LMS algorithm [Widrow1985] is used to update the filter parameters θ^l, $\overline{x_i^l}$ and σ_i^l. With the initial $\theta^l(0)$, $\overline{x_i^l}(0)$ and $\sigma_i^l(0)$ values determined in Step 2, the adaptive procedure is as following:

$$\theta^l(k) = \theta^l(k-1) + \alpha[d(k) - f_k]\frac{a^l(k-1)}{b(k-1)}$$

$$\overline{x_i^l}(k) = \overline{x_i^l}(k-1) + \alpha[d(k) - f_k]\frac{\theta^l(k-1) - f_k}{b(k-1)}a^l(k-1)\frac{x_i(k) - \overline{x_i^l}(k-1)}{(\sigma_i^l(k-1))^2}$$

$$\sigma_i^l(k) = \sigma_i^l(k-1) + \alpha[d(k) - f_k]\frac{\theta^l(k-1) - f_k}{b(k-1)}a^l(k-1)\frac{\left(x_i(k) - \overline{x_i^l}(k-1)\right)^2}{(\sigma_i^l(k-1))^3}$$

where $a^l(k-1) = \prod_{i=1}^{n} \exp[-\frac{1}{2}(\frac{x_i(k) - \overline{x_i^l}(k-1)}{\sigma_i^l(k-1)})^2]$, $b(k-1) = \sum_{l=1}^{M} a^l(k-1)$, $f_k = \frac{\sum_{l=1}^{M} \theta^l a^l(k-1)}{b(k-1)}$

and α is a small positive step-size. These equations are obtained by taking the gradient of L ignoring the expectation E (see chapter 2.2.5.1).

2.2.5.2. Influential parameters - meanings & interpretations:

The LMS algorithm is a gradient algorithm, i.e. a good choice of initial parameters θ^l, $\overline{x_i^l}$ and σ_i^l is very important to its convergence concerning accuracy and time. Since the error measure of this "back-propagation" algorithm is an extremely complicated function of all the parameters θ^l, $\overline{x_i^l}$ and σ_i^l, it can have numerous local minima. Depending on the initial parameter estimates, this algorithm always leads to the nearest minimum, i.e. it can become stuck in a local minimum of the error measure.

Recall that this filter is constructed based on linguistic rules from our previous experiences and some arbitrary rules. Both sets of rules are updated during the LMS adaptation procedure of Step 4 by changing the parameters in the direction of minimizing L.

In other words, the adaptation procedure can be directed to *the* local minimum we want (i.e. accuracy factor) and can converge quickly (i.e. time factor).

if these rules provide good instructions for how the filter should perform, that is, good description of the input-output pairs $[\underline{x}(k); d(k)]$.

The updating parameters θ^l[Mx1], $\overline{x_i^l}$[MxN] and σ_i^l[MxN] represent output means, input means and the input width of the Gaussian distributed data, respectively. The scalar output d is basically the label[14] of the test data[1xN] in numerical form, and σ_i^l describes how far the data from the output mean can be and still be assigned to it in an appropriate fuzzy form. M represents the number of the rules and N the number of the features, i.e. the dimension of the data. The parameter α is the "learning factor" or the step-size of training. It represents how fast and how smooth the training process proceeds.

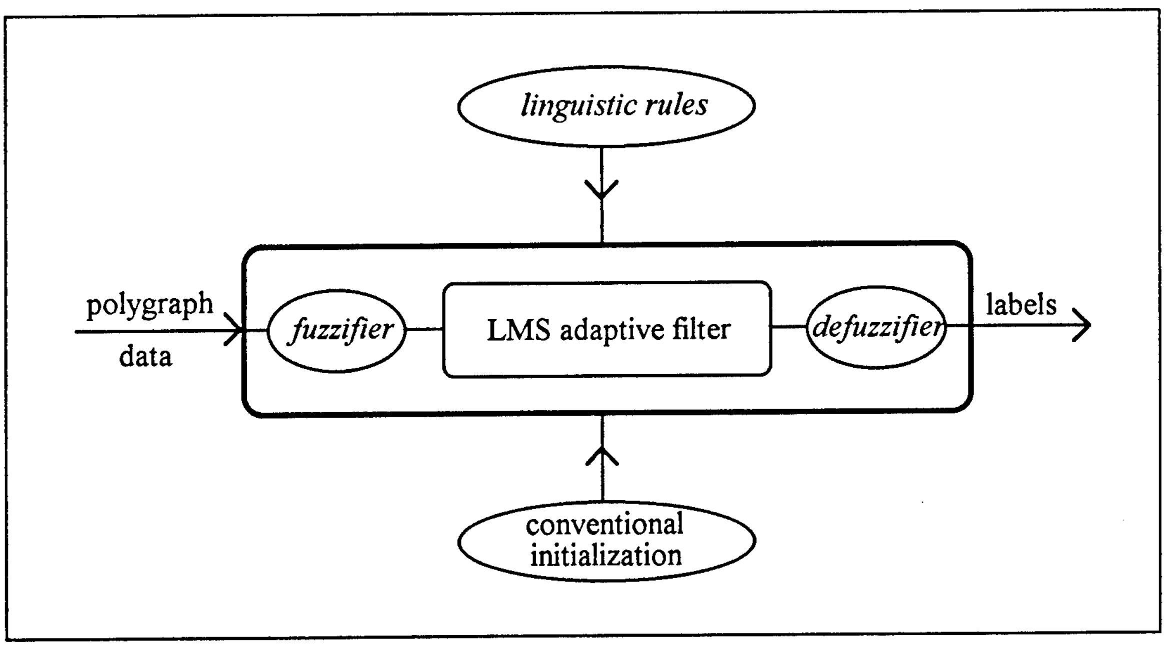


Fig.5: The LMS *fuzzy* adaptive filter used in this project

[14]"deceptive" or "non-decptive".

§3. APPROACH

3.1. Part I - FCM

3.1.2. Initial stage (conditions and methods):

A primary component of every pattern recognition problem is feature extraction. And this is actually one of the most important and influential tasks for any successful approach.

In previous researches [Layeghi1993,1] [Jacobs1993] [Dastmalchi1993], students have already investigated a set of 669 features for each polygraph test session. They used these features to train, optimize and eventually classify the data by a fuzzy K-Nearest Neighbor algorithm (KNN).

In this project, I have used these same features in their original form. I have also selected their best features and feature combinations for initial tests of my algorithm and for comparison between fuzzy-CM, fuzzy LMS adaptive filter and the fuzzy KNN approach.

At this point, the question of consistency and transferability of the features - independent of the algorithm - became more significant. It turned out to be one part of this research[15].

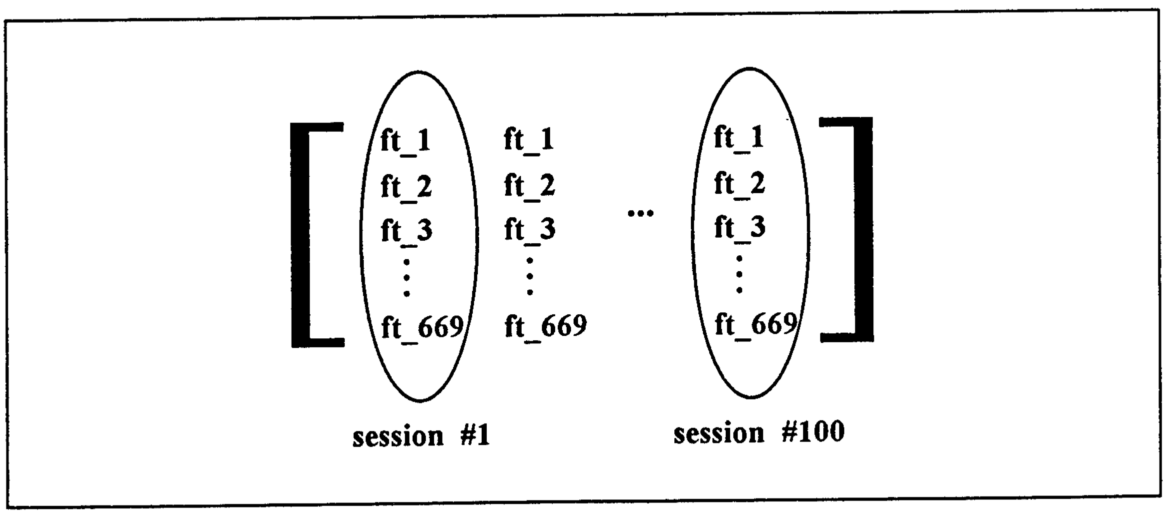


Fig.6: An example for a set of polygraph data as a matrix and its features used in this study

As mentioned earlier, each feature (total number=960) is extracted for all polygraph test *questions*, that is for relevant, irrelevant and control questions. It was, however, decided

[15]See also chapter 4.1.2.3.

not to use irrelevant questions in this study, because in a Controlled Question Polygraph Test comparison between the responses to relevant and control questions is the actual and most important factor.

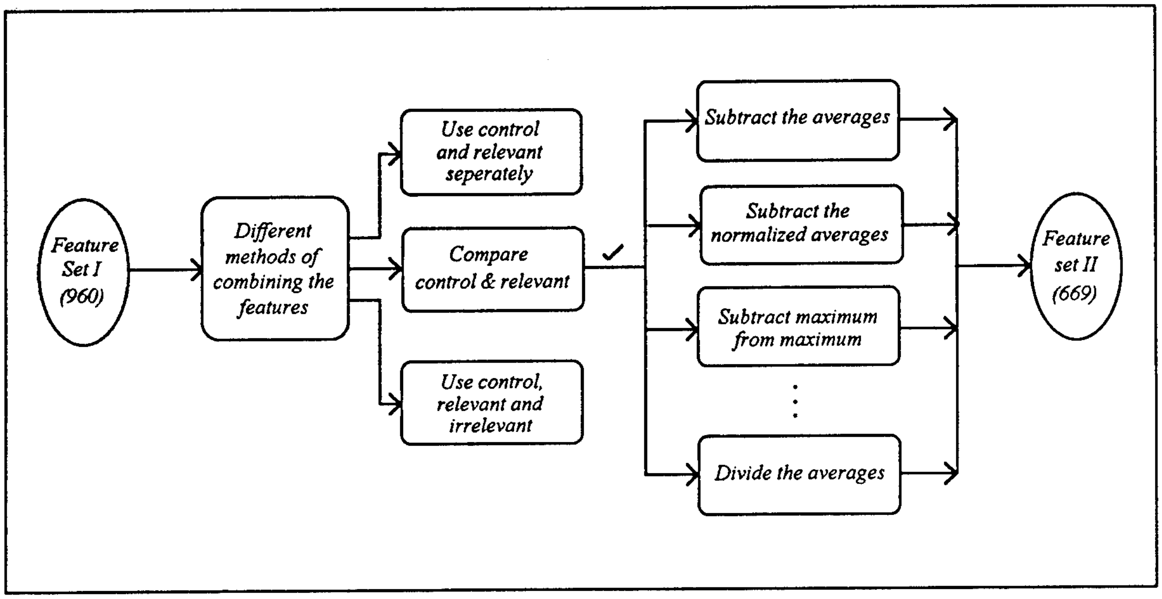


Fig.7: The original feature combinations

The Total number of the features for every test *session* at this stage is 669. Each set contains the same non-deceptive files but different deceptive ones. For more specific details about how the feature extraction was processed, and about combination methods which narrowed the total number from 960 to 669, see the references mentioned above.

3.1.3. Clustering stage

3.1.3.1. One-dimensional search and selection of the "best" single features:

After implementation and initial tests of the FCM-code, I began with the one-dimensional clustering (using *one* feature for all sessions). I used three sets (polydat_1, polydat_2, polydat_3) of such structured data as shown in Fig.42 containing 100 data elements, i.e. 50 truthful and 50 deceptive files. With these data, we ran 669 one-dimensional clustering searches containing 100 different one-dimensional data points at each time. As a result, we attained 669 times 2 clusters for each polydat_i.

After running these tests and evaluating them, I decided to select four sets of "best" one-dimensional features out of each polydat_i in preparation for the multi-dimensional clustering search. This decision was necessary to narrow the number of features, since it is impractical to find the best combination (concerning the quantity and the quality)[16] out of this immense number of features by an exhaustive way of searching.

For example, chosing only 4 or less feature-tuples from a set of 669 by trying all the possible different combinations needs the following number of computations:

$$\sum_{i=1}^{4} \binom{669}{i} = \sum_{i=1}^{4} \frac{669!}{i!(669-i)!} \approx 10^{10}.$$

The other challenge while finding good feature combinations is the problem of *single* features which yield poor results by one-dimensional clustering, but when used in *combination* with other features yield very good[17] results.

To narrow the amount of possible features, I decided to select the following four sets of single features with different performances.

	percentage of right detections in		
	deceptive files		*non-deceptive files*
group 1	≥ 60%	&	≥ 60%
group 2	≥ 80%	&	≥ 50%
group 3	≥ 50%	&	≥ 80%
group 4a	≥ 98%	&	no constraints
group 4b	no constraints	&	≥ 98%

Fig.8: Selected features by using one-dimensional FCM

The threshold of 60% was chosen, because any other value below or above that limit would again give us either too many or not enough features. Furthermore, any other value

[16]That means: How many features and which ones should be taken in a combination.
[17]"Good" or "poor" in sense of the definition in chapter 1.1.2.

closer to the limit 50% for both deceptive and non-deceptive files would be only a *random* clustering process. Yet, this decision was not enough. We would have lost some good features which provide correct detections - better than 80% - for at least one of the files. The fourth group was chosen to enable us to consider some extreme cases.

As an additional set of one-dimensional features, I chose those with good results in multi-dimensional tests[18] for *one* of the polydat_i's, and used them also for the other two polydat_i's, even though they didn't belong to one of the four feature sets mentioned above. This set was important to fulfill the constraint of consistency and transferability for any chosen polygraph data[19].

---

[18]See chapter 3.1.3.2.
[19]See the comparison in chapter 4.1.2.3.

Σ=669

ft_#	w-dcp #	dcp-ok %	w-non #	non-ok %	iter_#
1.0000	12.0000	76.0000	9.0000	82.0000	13.0000
2.0000	37.0000	26.0000	44.0000	12.0000	15.0000
3.0000	16.0000	68.0000	10.0000	80.0000	14.0000
4.0000	12.0000	76.0000	18.0000	64.0000	15.0000
5.0000	15.0000	70.0000	16.0000	68.0000	16.0000
6.0000	38.0000	24.0000	27.0000	46.0000	15.0000
7.0000	48.0000	4.0000	0	100.000	40.0000
8.0000	22.0000	56.0000	9.0000	82.0000	8.0000
9.0000	22.0000	56.0000	8.0000	84.0000	13.0000
10.0000	22.0000	56.0000	11.0000	78.0000	38.0000
11.0000	0	100.000	33.0000	34.0000	26.0000
12.0000	20.0000	60.0000	15.0000	70.0000	6.0000
13.0000	46.0000	8.0000	26.0000	48.0000	10.0000
14.0000	22.0000	56.0000	11.0000	78.0000	16.0000
15.0000	12.0000	76.0000	9.0000	82.0000	27.0000
16.0000	37.0000	26.0000	44.0000	12.0000	17.0000
17.0000	16.0000	68.0000	10.0000	80.0000	25.0000
18.0000	12.0000	76.0000	17.0000	66.0000	37.0000
19.0000	15.0000	70.0000	16.0000	68.0000	40.0000
20.0000	38.0000	24.0000	27.0000	46.0000	34.0000
21.0000	48.0000	4.0000	0	100.000	31.0000
22.0000	12.0000	76.0000	14.0000	72.0000	25.0000
23.0000	10.0000	80.0000	45.0000	10.0000	20.0000
24.0000	21.0000	58.0000	15.0000	70.0000	23.0000
25.0000	18.0000	64.0000	24.0000	52.0000	29.0000
26.0000	24.0000	52.0000	19.0000	62.0000	18.0000
27.0000	12.0000	76.0000	23.0000	54.0000	22.0000
28.0000	46.0000	8.0000	2.0000	96.0000	35.0000
29.0000	18.0000	64.0000	9.0000	82.0000	28.0000
30.0000	12.0000	76.0000	10.0000	80.0000	14.0000
		...			
447.0000	17.0000	66.0000	36.0000	28.0000	17.0000
448.0000	7.0000	86.0000	40.0000	20.0000	25.0000
449.0000	16.0000	68.0000	11.0000	78.0000	15.0000
450.0000	12.0000	76.0000	9.0000	82.0000	15.0000
451.0000	13.0000	74.0000	18.0000	64.0000	20.0000
452.0000	5.0000	90.0000	20.0000	60.0000	13.0000
453.0000	18.0000	64.0000	18.0000	64.0000	12.0000
		...			
662.0000	27.0000	46.0000	34.0000	32.0000	9.0000
663.0000	16.0000	68.0000	30.0000	40.0000	9.0000
664.0000	21.0000	58.0000	37.0000	26.0000	17.0000
665.0000	31.0000	38.0000	23.0000	54.0000	14.0000
666.0000	34.0000	32.0000	17.0000	66.0000	45.0000
667.0000	25.0000	50.0000	28.0000	44.0000	20.0000
668.0000	15.0000	70.0000	37.0000	26.0000	12.0000
669.0000	15.0000	70.0000	39.0000	22.0000	11.0000

Feature number: **ft_#**
\# of wrong results in decept. data: **w-dcp**
% right detection in decept. data: **dcp-ok**
\# of wrong results in truthful data: **w-non**
% right detection in truthful data: **non-ok**
Iterations_# for each feature: **iter_#**

Fig.9: An example for one-dimensional clustering

ft_#	w-dcp #	dcp-ok %	w-non #	non-ok %	iter_#
1.0000	12.0000	76.0000	9.0000	82.0000	13.0000
3.0000	16.0000	68.0000	10.0000	80.0000	14.0000
4.0000	12.0000	76.0000	18.0000	64.0000	15.0000
5.0000	15.0000	70.0000	16.0000	68.0000	16.0000
12.0000	20.0000	60.0000	15.0000	70.0000	6.0000
15.0000	12.0000	76.0000	9.0000	82.0000	27.0000
17.0000	16.0000	68.0000	10.0000	80.0000	25.0000
18.0000	12.0000	76.0000	17.0000	66.0000	37.0000
19.0000	15.0000	70.0000	16.0000	68.0000	40.0000
22.0000	12.0000	76.0000	14.0000	72.0000	25.0000
29.0000	18.0000	64.0000	9.0000	82.0000	28.0000
30.0000	12.0000	76.0000	10.0000	80.0000	14.0000
31.0000	14.0000	72.0000	16.0000	68.0000	21.0000
33.0000	18.0000	64.0000	16.0000	68.0000	14.0000
36.0000	15.0000	70.0000	8.0000	84.0000	14.0000
37.0000	8.0000	84.0000	13.0000	74.0000	15.0000
38.0000	12.0000	76.0000	14.0000	72.0000	18.0000
39.0000	14.0000	72.0000	13.0000	74.0000	17.0000
40.0000	16.0000	68.0000	15.0000	70.0000	13.0000
50.0000	17.0000	66.0000	17.0000	66.0000	18.0000
52.0000	15.0000	70.0000	20.0000	60.0000	23.0000
68.0000	13.0000	74.0000	18.0000	64.0000	17.0000
70.0000	20.0000	60.0000	20.0000	60.0000	23.0000
82.0000	16.0000	68.0000	20.0000	60.0000	12.0000
141.0000	17.0000	66.0000	17.0000	66.0000	15.0000
155.0000	17.0000	66.0000	17.0000	66.0000	25.0000
176.0000	16.0000	68.0000	18.0000	64.0000	13.0000
177.0000	16.0000	68.0000	16.0000	68.0000	13.0000
197.0000	13.0000	74.0000	17.0000	66.0000	15.0000
200.0000	17.0000	66.0000	13.0000	74.0000	12.0000
211.0000	13.0000	74.0000	16.0000	68.0000	42.0000
214.0000	17.0000	66.0000	12.0000	76.0000	27.0000
216.0000	15.0000	70.0000	14.0000	72.0000	32.0000
235.0000	15.0000	70.0000	19.0000	62.0000	14.0000
395.0000	18.0000	64.0000	17.0000	66.0000	10.0000
449.0000	16.0000	68.0000	11.0000	78.0000	15.0000
450.0000	12.0000	76.0000	9.0000	82.0000	15.0000
451.0000	13.0000	74.0000	18.0000	64.0000	20.0000
452.0000	5.0000	90.0000	20.0000	60.0000	13.0000
453.0000	18.0000	64.0000	18.0000	64.0000	12.0000
458.0000	16.0000	68.0000	14.0000	72.0000	8.0000
459.0000	20.0000	60.0000	10.0000	80.0000	10.0000
460.0000	14.0000	72.0000	18.0000	64.0000	9.0000
462.0000	14.0000	72.0000	17.0000	66.0000	7.0000
600.0000	18.0000	64.0000	20.0000	60.0000	37.0000

$\Sigma=45$

Feature number: **ft_#**
\# of wrong results in decept. data: **w-dcp**
% right detection in decept. data: **dcp-ok**
\# of wrong results in truthful data: **w-non**
% right detection in truthful data: **non-ok**
Iterations_# for each feature: **iter_#**

Fig.10: An exmple for the first group of selected features (representing group #1 at page)

3.1.3.2. Multi-dimensional search for the best feature combination:

3.1.3.2.1.Overview:

Having obtained these four sets of features, a multi-dimensional searching process through all of them was initiated to find the best feature combinations (concerning the quantity and the quality[20]).

Even though the number of the features[21] has already been narrowed, it is still impractical to do an exhaustive search, since the total number of the features contained in these four sets is about 100 for each polydat_i. In other words, the following number of computations is still needed for calculation of all 4 or less possible feature-tuples:

$$\sum_{i=1}^{4} \binom{100}{i} = \sum_{i=1}^{4} \frac{100!}{i!(100-i)!} \approx 4.0 \cdot 10^6 .$$

At this stage, I decided to investigate 3 different search methods to bypass the exhaustive way. They are

1. *random* search without duplication of any feature within a tuple,
2. *pseudo-exhaustive* search with the option of duplication and finally
3. *genetic* search with "uncontrollable" possibility of duplications.

In previous research projects [Layeghi1993,1] [Dastmalchi1993] [Jacobs1993], it was decided to narrow the feature numbers from 669 to 30 "best" ones and then an exhaustive search was run for up to four- or five-tuple combinations. In other words, their strategy was completely different than the aforementioned three strategies.

As mentioned before a "poor" or an average *single* feature by one-dimensional clustering might give us in *combination* with other features very good or even better results by a multi-dimensional clustering than any of them individually.

This fact was totally neglected by the feature selection methods used in the previous researches[22] [Laueghi1993,1] [Dastmalchi1993].

---

[20]That means: How many features and which ones should be taken in a combination.

[21]See chapter 3.1.3.1.

[22]See chapter 4.3. comparison for more details about differences between this and previous works.

Applying these three new strategies, I was able to consider more possible features for a multi-dimensional clustering than in previous works, without using the impractical exhaustive method.

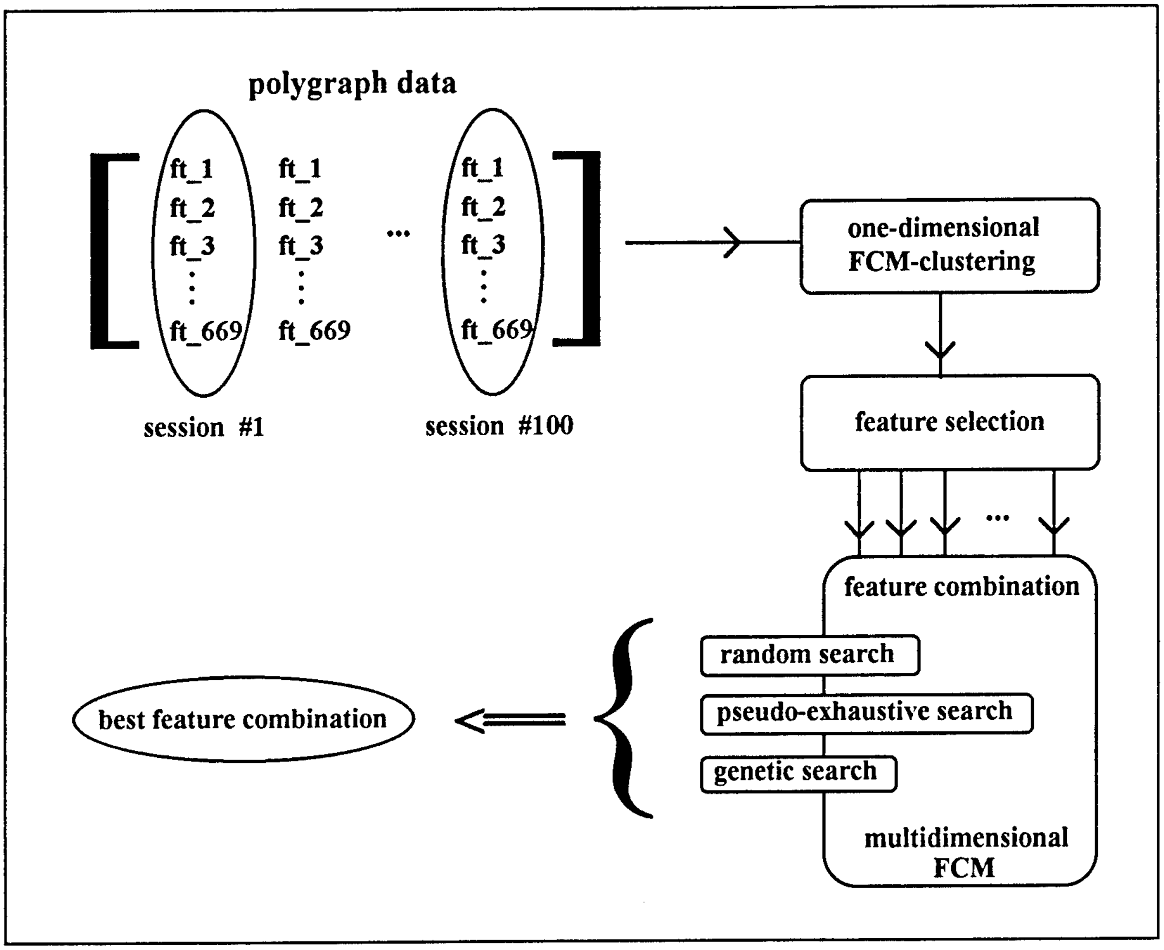


Fig.11: General search to find the best feature combination

3.1.3.2.2. Random search method:

Applying this method, an average of 14 to 20 different features out of the aforementioned four sets were taken, and then the FCM algorithm including the evaluation program for randomly chosen 4-tuples were run. After about 1000 combinations were constructed, I then picked out the best features and their combinations, and replaced the poor ones with new features. This same procedure was repeated until good[23] combinations were found.

[23] "Good" in sense of the definition in chapter 1.1.2.

Every time the results were out of balance - i.e. highly better detection either for deceptive or non-deceptive files by the cost of the other one - I appropriately took additional features from those four sets to eliminate the difference by improving the results of the worse file - and as much as possible - by maintaining the results of the better file.

After running this kind of tests several times, we were able to estimate which features are the good ones to combine together.

3.1.3.2.3. Pseudo-exhaustive search method:

Having some idea[24] which features are good in a combination with others[25], I built *every* possible four- to six-tuples out of those features and evaluated them. This method was very important to make sure that we did not lose any good combinations which might have been neglected by the random search.

I called this method *"pseudo"*-exhaustive, because each time it considers only a small part of the available features; but *"exhaustive"*, because it takes all the possible combinations within this part. Except for this major difference, all the other steps of this method are exactly the same as the random search.

3.1.3.2.4. Genetic search method:

This algorithm is basically a compromise between the pseudo-exhaustive and the random search method, plus a weighting system which supports those features with good results.

Initial populations of 200 to 300 chromosomes[26] are randomly created. Each chromosome is a combination of N features, where N stays constant for each population during the outgrowth. Each single feature is selected from a gene pool for the particular population that the individual belongs to. Each gene pool consists of twenty to forty features that we have chosen[27].

---

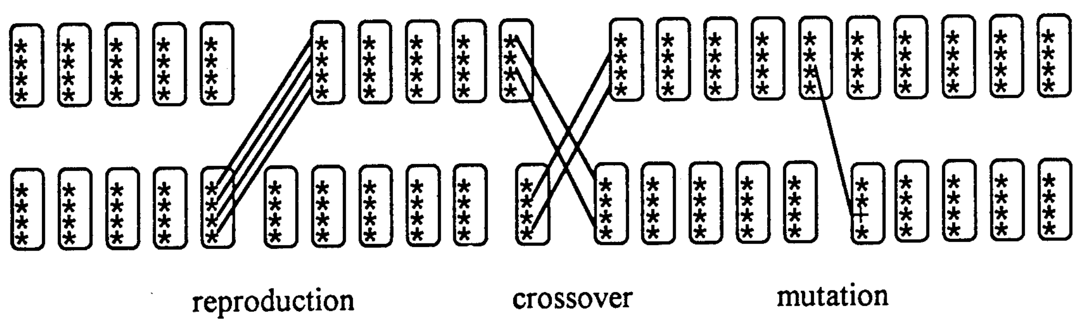
[24]By using the results of the random search method and also the 5th group mentioned at page 3.1.3.1.
[25]Remember the fact that some "poor" single features might give us in combination with others very good results
[26]Individuals or feature-tuples.
[27]Directed by our experience from using the random and the pseudo-exhaustive methods.

In this project three processes operate on the evolution[28] of each population:

- reproduction
- crossover
- mutation.

These three processes determine how each new generation will be created based on the old one. Before genetic reproduction, the fuzzy-c-means algorithm evaluates the percentage of correct deceptive and non-deceptive detections for each chromosome. The average of them is the fitness value of that chromosome. During the genetic reproduction, the chromosomes of the new generation are copied from the chromosomes of the old generation in a probabilistic sense. The probability that a particular chromosome will be copied is the ratio of that chromosome's fitness value against the total fitness values of the entire population of the old generation.

After selection, genetic crossover randomly chooses pairs of chromosomes as parents, splices them, and recombines them - by randomly mixing some of the parents genes - into pairs of offsprings. Finally, genetic mutation randomly substitutes a new gene within a randomly chosen chromosome. The extent to which crossover and mutation occur can be verified by appropriate initialization.



Number of feature tuples: 300
Number of features in each tuple: 4

Fig.12: An example for the genetic outgrowth with 4 genes (=features) in each chromosome (=individual)

[28]See chapter 4.1.2.2 for particular results of this method.

3.1.3.3. General process - Optimization by changing parameters:

Simultaneously to the search for the best features and their combinations, we were optimizing the system by changing and adjusting the parameters. Recall, the whole idea of this pattern recognition was to cluster the unlabeled data into two clusters which represent the deceptive and the truthful group[29].

Knowing the information of which files were deceptive or truthful[30], we were able to change the parameters in the way that the output could continuously come closer to the real cluster structure. This process is depicted in the following figure. The "fuzzy c-means algorithm" block not only represents the pure FCM algorithm shown in Fig.3, but also the general search for good features shown in Fig.11 which ran simultaneously with the optimization process.

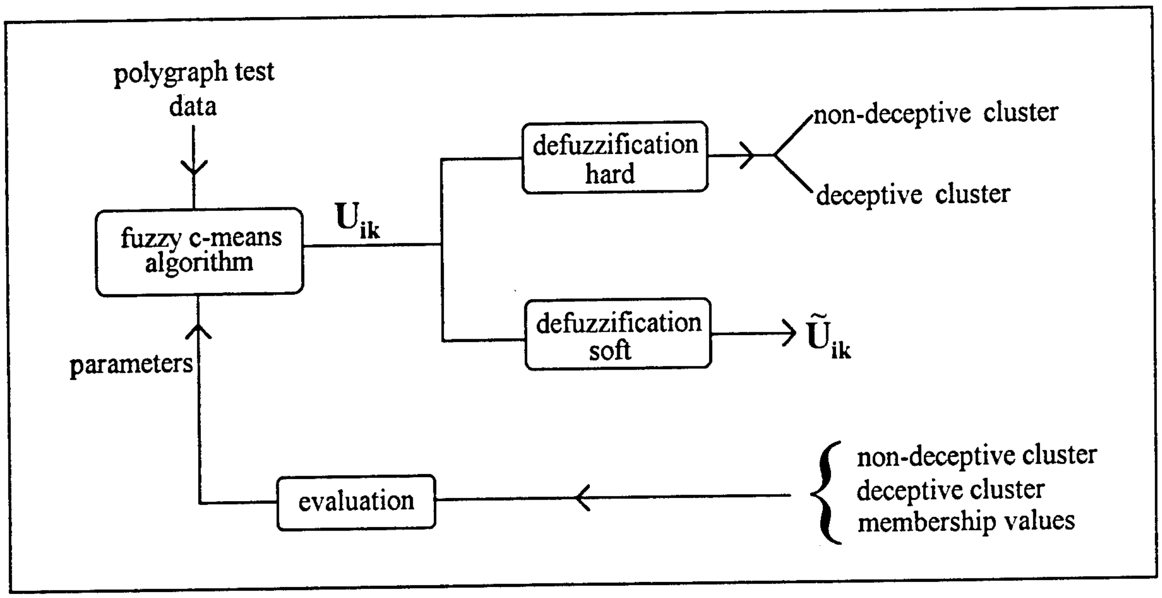


Fig.13: Optimization of the clustering environment
- General process -

As an example, I will briefly discuss how the parameter m was chosen and eventually modified: The weighting exponent m plays a significant role in this system. Since the control parameter m itself does not belong to the optimizing values within the iterative process of FCM algorithm, one must choose m before implementing the algorithm, and

[29]See chapter 3.1.2.
[30]We know this information beforehand for sure, because the subjects have confessed their case or the actual offender was found.

optimize it manually. There are several research papers written as an attempt to find the optimal m for different clustering problems.

The effect of m was discussed in [Bezdek1981]. Although Bezdek proposed heuristic guidelines for m, no *theoretical* basis for an optimal choice for *m* has been reported. The only known paper in this matter [Choe1992] proposed a method for determining m based on the concept of fuzzy decision theory initiated by [Zadeh1970].

But since the definition of "good" clusters in [Choe1992] did not exactly match to our clustering environment, I chose the "trail and error" strategy to find the optimal m by systematically increasing it. Fortunately, there is a logical limit[31] for this increasing process in our case, even though m can mathematically be any value from [2, ∞).

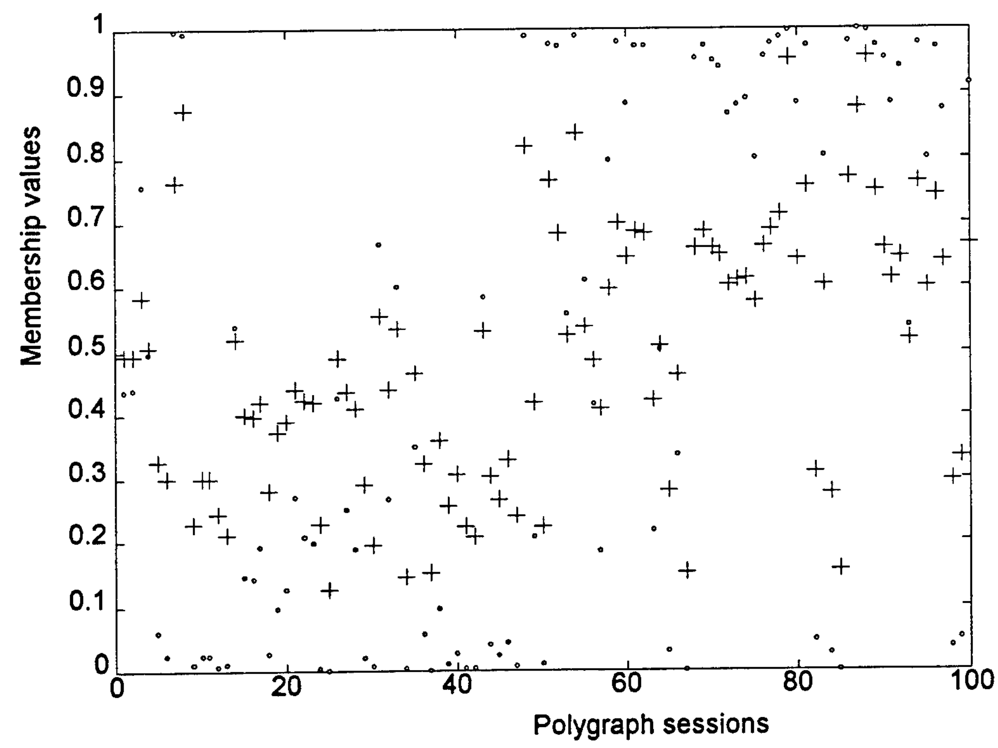


Fig.14: An example for the influence of 'm'

[31] See chapter 2.2.3.2. for the meaning of *m*.

For more details on this matter see the chapter 4.1.1. In Fig.14, you see an example for how the weighting exponent m influences the membership values for one of the features from polydat_3 in one-dimensional mode.

3.1.3.4. Evaluation strategy:

Due to the small number of non-deceptive cases available, each session for a subject was used as a separate and individual case. But in average, each group of three sessions belong to one person concerning the same crime, meaning the results of these sessions are not independent of each other. Using this additional information, the clustering system can come closer to the actual structure of the data, i.e. we can get a better performance.

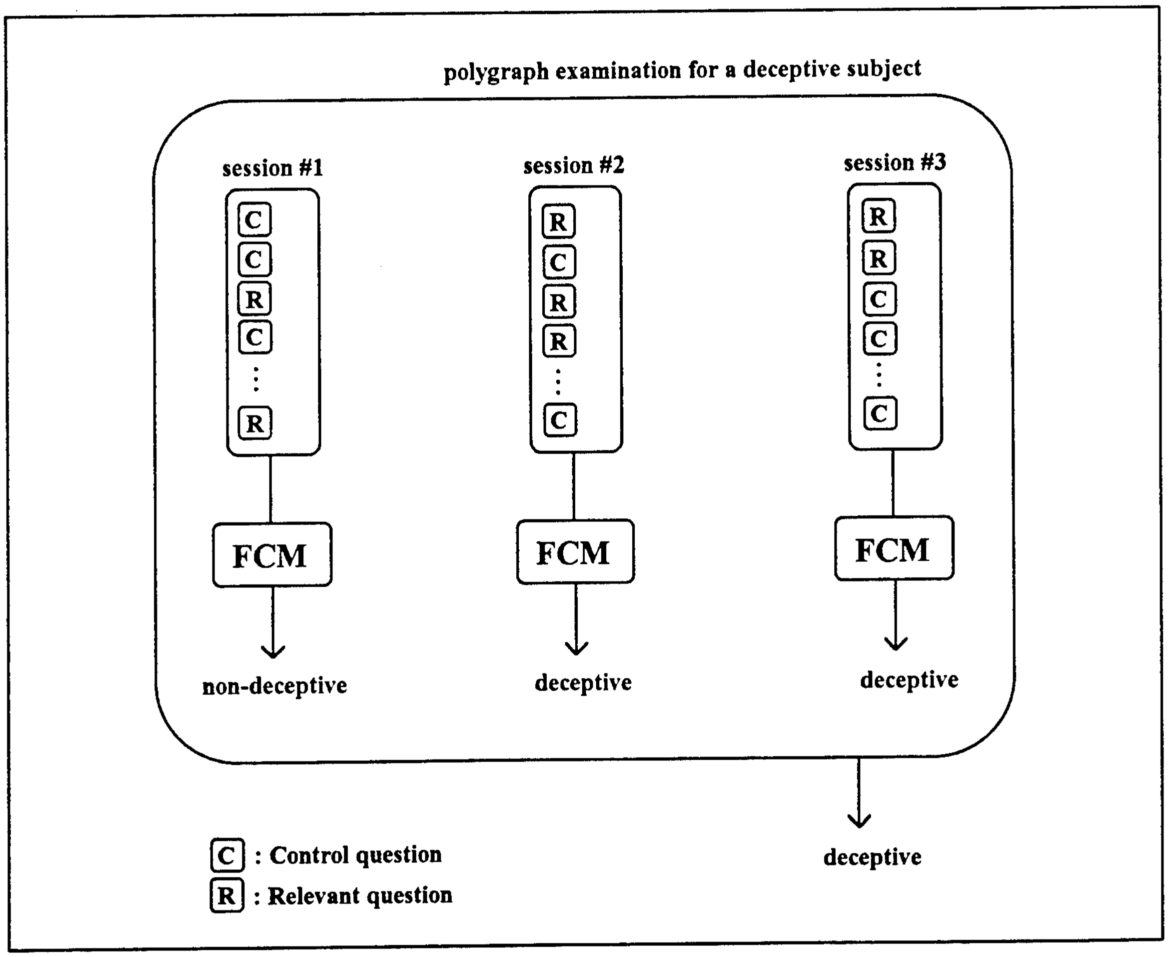


Fig.15: An example for the final evaluation using the dependency of the sessions

After clustering and evaluating[32] each session separately, some cases with different responses to the algorithm were found, although they belonged to one person. In circumstances like this, we combined the individual results within each group in a way that the majority response was assigned to the whole group (see Fig.15).

In those cases that each polygraph examination contains 2 or 4 test sessions where there is no majority response to build, I decided to take only those membership values further to the threshold 0.5. For example, by the feature combination [30, 30, 39, 235, 363, 450] used to cluster polydat_1, we obtained for one of the examination with four sessions the following membership values: 0.4164, 0.5519, 0.5377, 0.4780. After defuzzification we got 0, 1, 1, 0 where no majority class can be build. However, the second and the third membership values are closer to the threshold than the other two ones. With the aforementioned strategy, this examination is labeled with 0.

Recall that each polygraph examination has a set of control and relevant questions which is repeated an average of three times. The only difference between each session is the order in which the questions are asked.

[32]The general evaluation process is contructed as following:
After each clustering procedure (one- or multi-dimensional) a two-row vector of membership values is given which represent the two deceptive and non-deceptive clusters. The evaluation process takes the membership values of one these clusters and counts the values below and above the threshold 0.5. Thus, as a result we get the absolute number of wrong and right detections.

3.2. Part II - LMS fuzzy adaptive filter

3.2.1. Feature selection by visual inspection:

One advantage of a fuzzy logic system is its use of common sense human reasoning as inference rules. The fuzzy LMS algorithm we used extends this advantage by further optimizing such inference rules to "fit" a given set of data. To fully utilize the advantages of this fuzzy LMS algorithm, we had to face two issues: coming up with the proper intuitive rules for initialization and a set of data that reflects real-world examples for training.

As mentioned before, for practical reasons, the polygraph recognizer can use only a subset of the given 669 features, and we would have to choose the effective ones. Furthermore, the fuzzy logic system needed reasoning rules, operating on those features we selected, to analyze the data. We believed that we could visually inspect graphical plots of the feature data to learn about the feature information. Since fuzzy logic corresponds closely with human reasoning, we would then, based on the knowledge obtained from our visual inspection, select features that help differentiate deceptive and non-deceptive subjects and codify the patterns we would find into reasoning rules.

For the visual inspection, a scatter plot was made of the data in polydat_3 of each single feature. We looked at each plot individually. In any given plot, if the deceptive and non-deceptive subjects showed distinctive clusters, then the feature was considered good. If the elements of these two classes seemed to be randomly located, then the feature was considered bad. After viewing all 669 plots, we subjectively determined the following features[33] to be very good: 9, 11, 29, 164, 399, 449, 450, 451, 452, and 454; with 451 and 452 to be the best.

Initially the fuzzy adaptive filter was to be designed based on two features, with more features to be added in the future as the project progresses. We limited the feature couple to be composed of good features from the above list. Visual inspection was made of the scatter plots of the data in polydat_3 of various such feature combinations to determine the effective ones. While selecting feature couples, we again searched for combinations that show distinctive clusters for deceptive and non-deceptive subjects. The features

[33] See Fig.41 for the meaning of these numbers.

within a combination should also be uncorrelated with each other. A plot of the feature 449 and 450 combination shows that they are a bad couple because they seem to be linearly correlated[34], as the data points fall closely along a straight line.

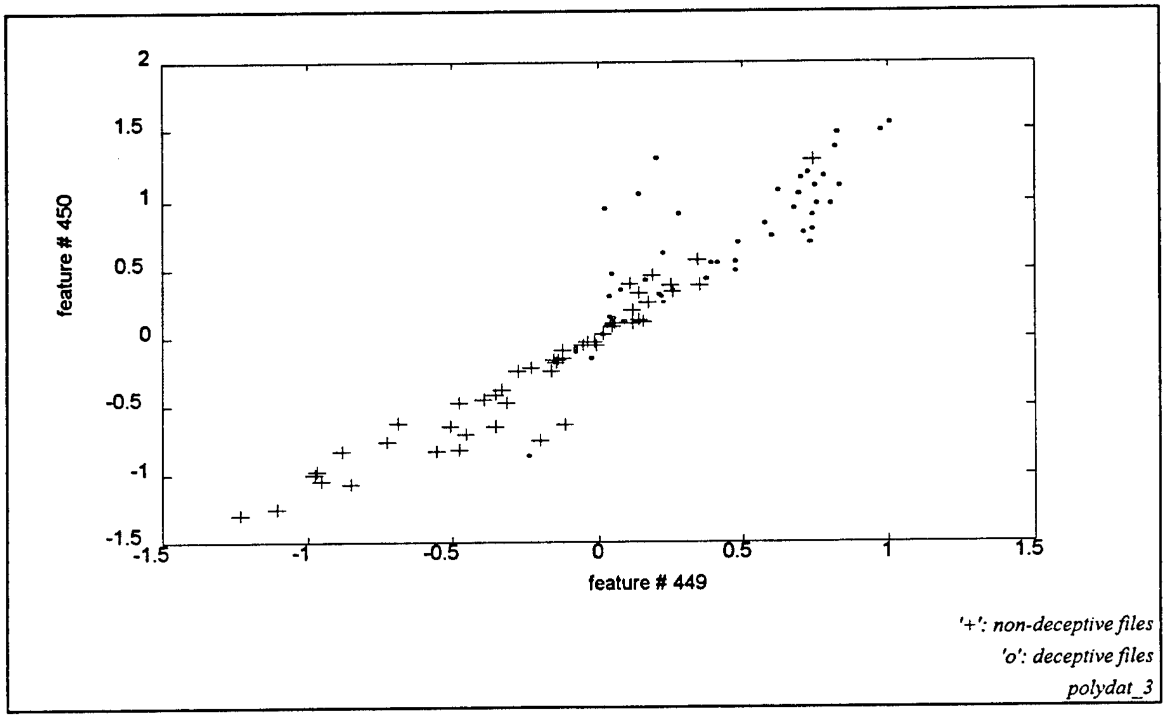


Fig.16: Scatter plots of two linearly correlated features

Visual inspection of feature couples consumed much more time than visual inspection of individual features, as the clusters took on more complicated shapes. Furthermore, in the fuzzy LMS algorithm each inference rule exerts influence centered in an elliptical contour where the major and minor axes are parallel with the axes of the feature plot. Clusters with a complicated shape must be built from those elliptical regions (see next figure). Therefore we had the additional task of finding clusters in the feature plots that could be easily approximated with few ellipses, to reduce system complexity.

Due to the lack of time, we did not examine the plots of all forty-five possible combinations of the ten very good features listed above. We only examined a random few. Based on the ones we did examine, we settled on the combination of features 451 and 452 because:

[34]Correlation between two features means that information in one is similar to the information in the other one, and using them together only introduces redundancy and hardly improves the system.

- they were the best - visually recognizable - features individually,
- they seemed uncorrelated with each other and
- we roughly found four elliptical clusters from the plot.

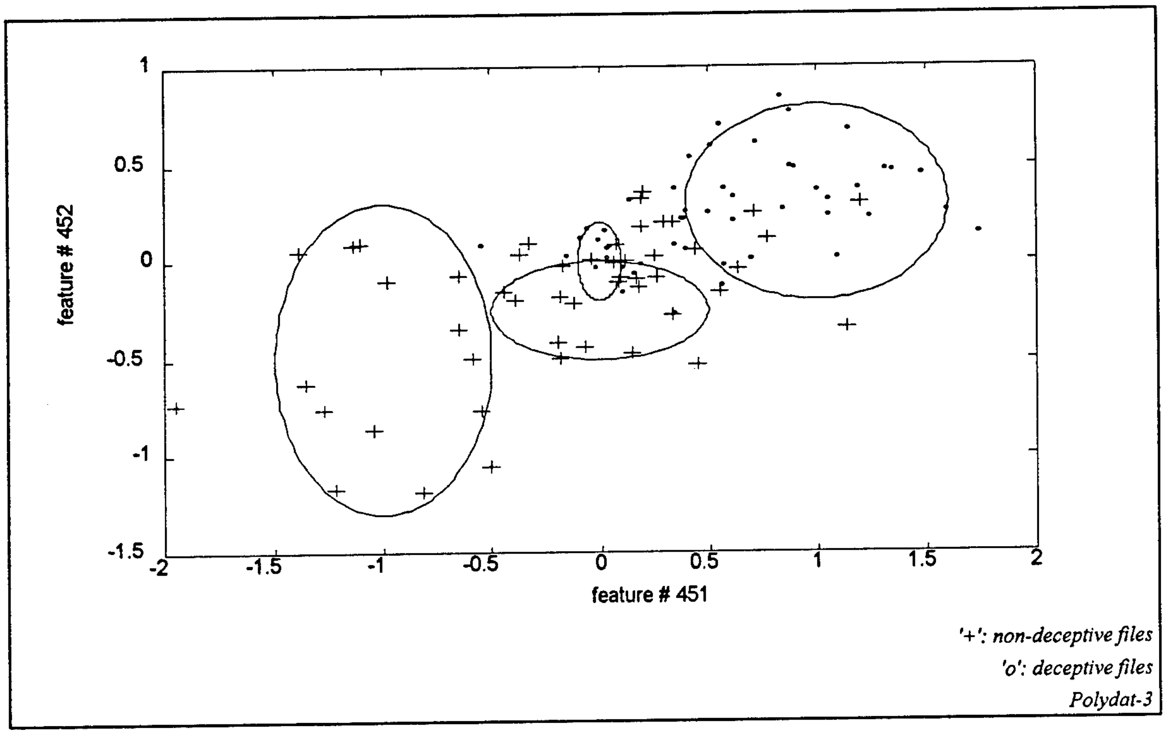


Fig.17: The four elliptical clusters used for setting the linguistic rules

3.2.2. Setting linguistic rules:

We initialized the fuzzy system such that it would exploit the knowledge we had just obtained about the clusters for features 451 and 452. There were two inputs, one for each feature, and four rules, one for each cluster. We had to represent those visual clusters we found with inference rules. The linguistic rules are shown in the following figure.

1. IF f1 is about -1 (±0.5) and f2 is about -0.5 (±0.8),
THEN decision is *non-deceptive* ⇒ output is +1.

2. IF f1 is about 0 (±0.5) and f2 is about -0.25 (±0.25),
THEN decision is *non-deceptive* ⇒ output is +1.

3. IF f1 is about 0 (±0.1) and f2 is about 0 (±0.2),
THEN decision is *deceptive* ⇒ output is -1.

4. IF f1 is about 1 (±0.6) and f2 is about 0.3 (±0.5),
THEN decision is *deceptive* ⇒ output is -1.

f1: measurement of feature # 451
f2: measurement of feature # 452

Fig.18: Initial linguistic rules for the fuzzy adaptive filter based on the clusters in Fig.17

The linguistic rules above were then translated to fuzzy membership functions as outlined in [Wang1994]. The xi's were the centers of the clusters; the sigmas were the widths of the clusters (±xxx in the above rules); and the thetas were either +1 or -1 for non-deception and deception, respectively.

The output of the fuzzy reasoning based on the above four rules would not be exactly +1 or -1. It would be within the range limited[35] by +1 and -1. For our project, we decided that a positive output denotes non-deception and a negative output denotes deception. In other words, the decision threshold was at zero.

[35] After training the output may go beyond that range.

For future investigations one may experiment with a different threshold[36].

The choice of plus and minus one for non-deception and deception is based on the following argument: The learning technique uses the squared error, which is the square of the difference between the desired output and actual output. In computing that squared error, if the difference between the desired output and actual output is greater than one, then the squaring operation expands the error value and therefore gives more significance to such mistakes. On the other hand, if the difference is less than one, than the squaring operation compresses the error value and therefore gives it less significance.

Given zero as the threshold between deception and non-deception and assuming the actual output would never go beyond plus two or minus two, then the choice of plus and minus one as desired outputs would mean that the error calculation gives more significance to misclassifications and less to correct classifications; Here classification refers to the crisp, defuzzified classification, not the degree of belonging.

For example, the desired output for non-deceptive subjects is plus one. If the actual output is between zero and two, then the crisp classification is non-deception, which is correct. The numerical difference between the actual output and the desired output is less than one in this case, and the squaring operation would lessen the significance of that error. On the other hand, if the actual output is less than zero, then the crisp classification would be deception, which is wrong. In that case, the numerical difference between the desired output and the actual output is greater than one and more significance would be given to such mistakes. Similar argument can be apply for the choice of minus one as the desired output for deceptive subjects.

3.2.3. Training, testing and evaluation strategy:

The fuzzy LMS algorithm can be optimized to a specific set of data. To exploit that aspect of the algorithm, we also selected a set of data to train the system. Following a procedure similar to one used in an earlier project with KNN classifying algorithm [Layeghi1993], we had 35 deceptive subjects and 35 non-deceptive subjects - from each polydat_i - for

[36]One may also view the output as a fuzzy value and map it to a confidence value in addition to just a deception/non-deception decision. That would differentiate a sure judgment from an unsure one and may be more helpful in practice.

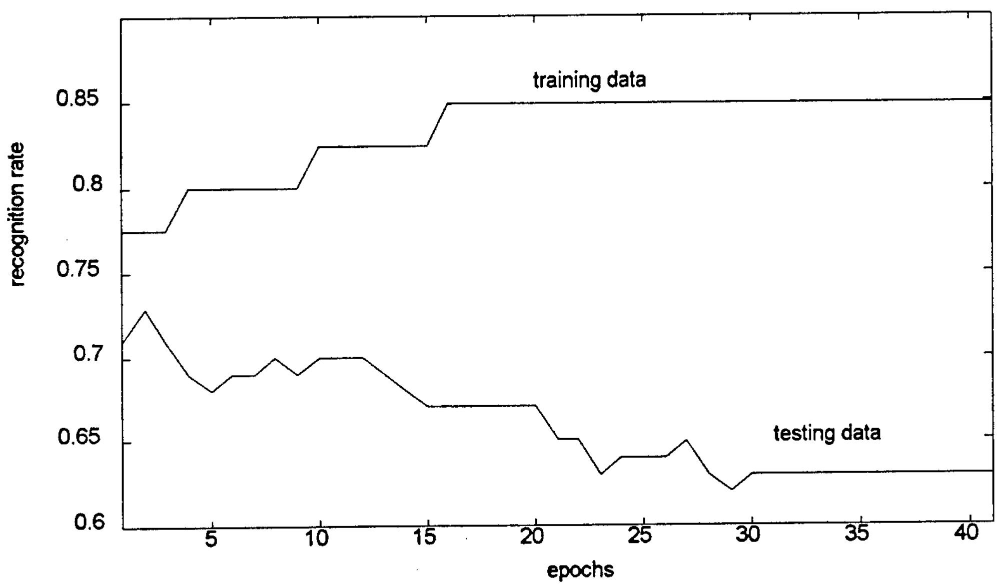
training. However, with a set of only 100 subjects within each polydat_i, that left a rather small amount for *testing* (i.e. 15 deceptive and 15 non-deceptive subjects). Therefore we also tested the algorithm with 10 deceptive subjects and 10 non-deceptive subjects for training and the rest (40 deceptive subjects and 40 non-deceptive subjects) for testing. That might be a bit extreme in the other direction, but we could interpolate the results and also see the sensitivity of the algorithm to the amount of training data.

We tested both cases for all three polydat_i's, giving a total of six tests. Each test was repeated twenty times. The training data were randomly chosen each time, and the rest of the available data in each set were used for testing. We recorded for each test the average of those twenty trials. This repeated testing was done to ensure that the results were not dependent on a particular choice of training data.

3.2.4. What to do with the memorizing problem?

Most learning algorithms suffer the dilemma of overlearning, or memorizing. Usually the problem occurs when the learning algorithm tries too hard at optimizing itself to a set of training data, sometimes to the point of memorizing them, such that it does not generalize to understand new data. Overlearning is exacerbated when the training data set is not completely representative of the testing set.

In a pattern recognition problem, while the recognition rate for the training data may increase steadily until it reaches a certain plateau, the recognition rate for testing data may only increase for a while, after which it may decrease until it hits a plane. We observed such phenomenon in our system:



The training data consist of twenty non-deceptive subjects and twenty deceptive subjects from polydat_3.
The testing data consist of all one hundred subjects from polydat_1.

Fig.19: An example for memorizing as the system "learns"

The point where the recognition rate starts to decrease marks the beginning of overlearning. In practical applications, most adaptive learning algorithms are trained only to the point before overlearning occurs, when the performance on the testing data reaches its peak.

In our testing we had taken that approach and, for each trial, the percentage of correct recognition was taken as the maximum attained for the testing data within forty epochs[37].

We disregarded the recognition rate for the training data because for many systems, including our own, a proper set-up could easily attain a recognition rate of 100%. That is, the recognition rate of the training data bears little importance in practical applications.

[37] An epoch is defined as one complete cycle through all the training data.

§4. RESULTS AND CONCLUSIONS

4.1. Fuzzy-c-means

4.1.1. Searching for the best level of fuzziness (parameter 'm'):

One of the major steps during the one-dimensional clustering was the searching process for the best value of m[38]. For this process, it was necessary to run the FCM algorithm for different m's and for different data by increasing m systematically. This was done for all 669 features and for each polydat_i, by every new m.

Recall that it was decided to consider four groups of features to limit the feature pool for multi-dimensional clustering. Even though the general development - while changing m - was similar for each polydat_i, the individual reaction of these 4 groups within each polydat_i was a little different. For the final decision, we considered all these variances, correct detection rates and also the distributions of the membership values for each m.

In the following, I will mention some of the remarkable observations we have made during this process (see also the following tables and figures representing the results of polydat_3):

As expected, the membership values U_{ik} did approach the 0.5-level[39] by increasing m, i.e. the results became fuzzier. Thus, we had to limit the increasing process to avoid the uncertainty of the results caused by too much "fuzziness" (which means that every person belongs to both clusters with almost the same possibility). However, we could observe a very interesting phenomenon. Even though the membership values came closer to 0.5, and the distances for different persons to this level were around 10^{-x} (with $x > 3$), they were still visually recognizable as deceptive and truthful clusters.

See the following two figures and also the Fig.14 for examples. Notice that the first 50 sessions represent the non-deceptive persons and the other 50 the deceptive ones.

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[38]See also chapter 3.1.3.3. for the discussion about finding the best m.
[39]See chapter 2.2.3.2. for more details.

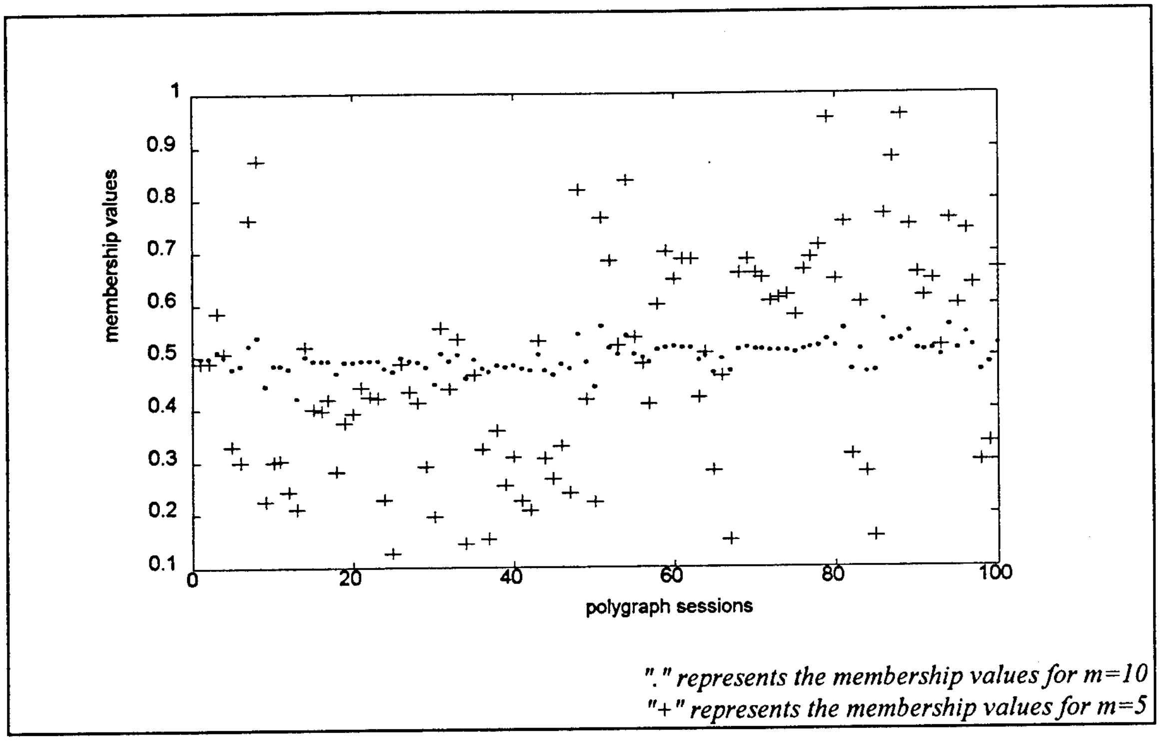

Fig.20: Influence of increasing 'm' for polydat-3 session #1

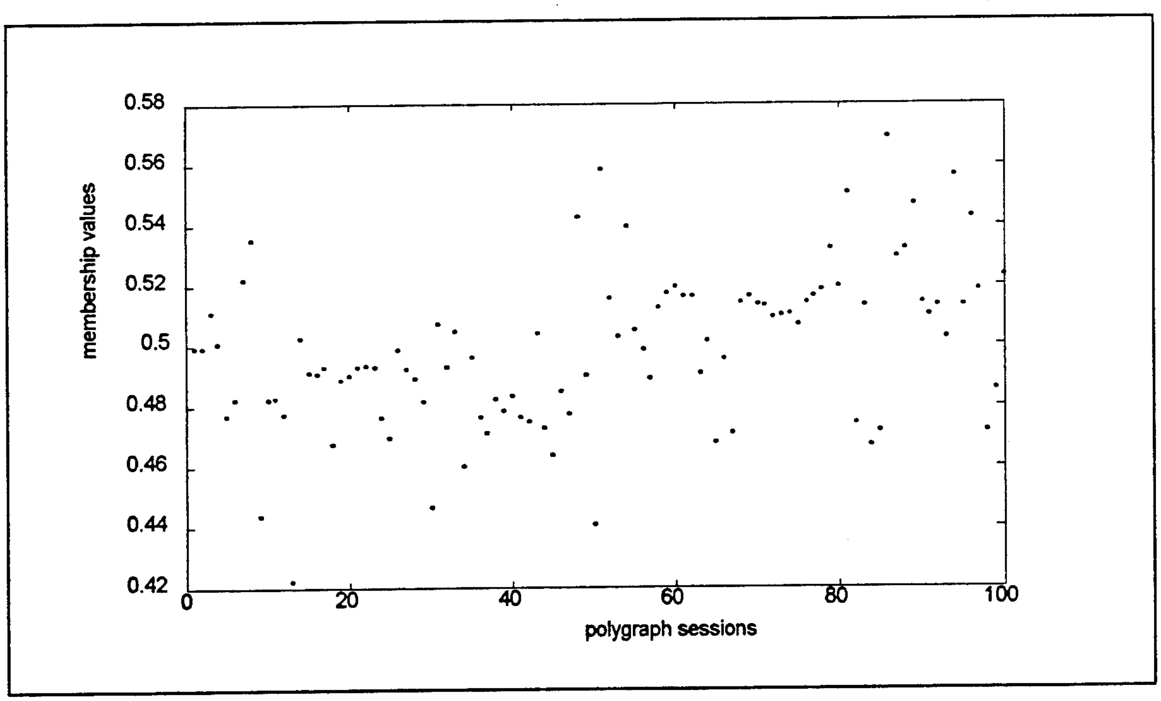

Fig.21: The zoomed-in view of the above figure for m=10

In the following two tables, the influence of changing *m* (for polydat_3/group #1, as an example) is depicted. As mentioned earlier this group represents those features which give us better than 60% right detection for both deceptive and non-deceptive files by one-dimensional clustering.

As you see in these examples, while increasing the parameter *m*, new "good" features appear. Some old ones provide even better detection rates and some get worse or even disappear. This progress is not unlimited. As you see, the development from 'm=4' to 'm=5' is smoother than between 'm=2' and 'm=4' regardless of 'm=3' step. By continuing this process above 'm=5', the tendency becomes rather negative.

Those features marked with (*) represent a better detection rate than 75% at least in one of the two clusters. Notice that these features also change during the increasing process of *m*. By continuing this process above 'm=5', also this tendency becomes rather negative.

After considering the other groups[40] and their development for each polydat_i, 'm=5' appeared to be the best compromise. Notice that there is also an outstanding result for feature number 452 by 'm=5' (see Fig.23). That was the only *inidividual* feature ever by an one-dimensional clustering process with a correct detection rate of 90% for non-deceptive files.

Another interesting aspect is that independent of *m*, the conglomeration areas where "good" features appear are always the same: For example the half of the "good" features are among the first hundred, but between 200 and 300, there is only one.

In the next tables we will use the following abbreviations:

ft #:	Feature number.
w_dcp:	Wrong detection within the deceptive cluster in percent.
w_non:	Wrong detection within the non-deceptive cluster in percent.
***:**	Features with a better detection rate than 75% at least in one of the two clusters.

'm=...' ***MINUS*** **'m=...':** Represents the difference in detection rates by using different *m*'s.

[40]See Fig.8.

polydat_3

group #1 & m=4				'm=2' *MINUS* 'm=4'	
ft #	w_dcp	w_non		%	%
1.0000	24.0000	18.0000	*	0	-2.0000
3.0000	32.0000	20.0000	*	2.0000	0
4.0000	22.0000	36.0000	*	---------new feature--------	
5.0000	30.0000	32.0000		2.0000	0
12.0000	40.0000	30.0000		---------new feature--------	
15.0000	24.0000	18.0000	*	0	-2.0000
17.0000	32.0000	20.0000	*	2.0000	0
18.0000	22.0000	36.0000	*	---------new feature--------	
19.0000	30.0000	32.0000		4.0000	0
22.0000	24.0000	28.0000	*	0	0
29.0000	36.0000	18.0000	*	0	0
30.0000	24.0000	20.0000	*	-2.0000	4.0000
31.0000	28.0000	32.0000		-2.0000	0
33.0000	36.0000	32.0000		0	0
36.0000	30.0000	16.0000	*	0	0
37.0000	16.0000	26.0000	*	0	4.0000
38.0000	24.0000	28.0000	*	0	0
39.0000	28.0000	26.0000		-6.0000	4.0000
40.0000	32.0000	30.0000		0	0
50.0000	34.0000	34.0000		2.0000	0
52.0000	30.0000	40.0000		---------new feature--------	
68.0000	24.0000	36.0000	*	---------new feature--------	
70.0000	40.0000	40.0000		-2.0000	0
82.0000	32.0000	40.0000		---------new feature--------	
141.0000	34.0000	34.0000		-4.0000	0
155.0000	34.0000	34.0000		-4.0000	0
176.0000	32.0000	36.0000		---------new feature--------	
177.0000	32.0000	32.0000		0	0
197.0000	26.0000	32.0000		0	2.0000
200.0000	34.0000	26.0000		-2.0000	0
202.0000	30.0000	28.0000		0	0
211.0000	26.0000	32.0000		0	0
214.0000	32.0000	26.0000		0	0
216.0000	30.0000	28.0000		0	0
235.0000	30.0000	38.0000		-4.0000	2.0000
395.0000	38.0000	32.0000		---------new feature--------	
449.0000	32.0000	20.0000	*	0	6.0000
450.0000	24.0000	18.0000	*	0	2.0000
451.0000	24.0000	38.0000	*	---------new feature--------	
453.0000	36.0000	36.0000		0	0
458.0000	32.0000	26.0000		6.0000	-2.0000
459.0000	40.0000	18.0000	*	---------new feature--------	
460.0000	26.0000	38.0000		---------new feature--------	
462.0000	28.0000	34.0000		0	0
600.0000	36.0000	40.0000		0	0

for the abbreviations see page 46

Fig.22: Comparison between the results for 'm=2' and 'm=4'

polydat_3

group #1 & m=5				'm=4' *MINUS* 'm=5'	
ft #	w_dcp	w_non		%	%
1.0000	24.0000	18.0000	*	0	0
3.0000	32.0000	20.0000	*	0	0
4.0000	24.0000	36.0000	*	-2.0000	0
5.0000	30.0000	32.0000		0	0
12.0000	40.0000	30.0000		0	0
15.0000	24.0000	18.0000	*	0	0
17.0000	32.0000	20.0000	*	0	0
18.0000	24.0000	34.0000	*	-2.0000	2.0000
19.0000	30.0000	32.0000		0	0
22.0000	24.0000	28.0000	*	0	0
29.0000	36.0000	18.0000	*	0	0
30.0000	24.0000	20.0000	*	0	0
31.0000	28.0000	32.0000		0	0
33.0000	36.0000	32.0000		0	0
36.0000	30.0000	16.0000	*	0	0
37.0000	16.0000	26.0000	*	0	0
38.0000	24.0000	28.0000	*	0	0
39.0000	28.0000	26.0000		0	0
40.0000	32.0000	30.0000		0	0
50.0000	34.0000	34.0000		0	0
52.0000	30.0000	40.0000		0	0
68.0000	26.0000	36.0000		-2.0000	0
70.0000	40.0000	40.0000		0	0
82.0000	32.0000	40.0000		0	0
141.0000	34.0000	34.0000		0	0
155.0000	34.0000	34.0000		0	0
176.0000	32.0000	36.0000		0	0
177.0000	32.0000	32.0000		0	0
197.0000	26.0000	34.0000		0	-2.0000
200.0000	34.0000	26.0000		0	0
211.0000	26.0000	32.0000		0	0
214.0000	34.0000	24.0000	*	-2.0000	2.0000
216.0000	30.0000	28.0000		0	0
235.0000	30.0000	38.0000		0	0
395.0000	36.0000	34.0000		2.0000	-2.0000
449.0000	32.0000	22.0000	*	0	-2.0000
450.0000	24.0000	18.0000	*	0	0
451.0000	26.0000	36.0000		-2.0000	2.0000
452.0000	10.0000	40.0000	*	-----new feature-----	
453.0000	36.0000	36.0000		0	0
458.0000	32.0000	28.0000		0	-2.0000
459.0000	40.0000	20.0000	*	0	-2.0000
460.0000	28.0000	36.0000		-2.0000	2.0000
462.0000	28.0000	34.0000		0	0
600.0000	36.0000	40.0000		0	0

----feature # 202 is missing----

for the abbreviations see page 46

Fig.23: Comparison between the results for 'm=4' and 'm=5'

4.1.2. Searching for the best feature combination:

4.1.2.1. Results of the conventional methods and general observations:

As mentioned in chapter 3.1.3.2.1, we decided for three different strategies to find out the best feature combination that can represent the two sought clusters within the polygraph data.

After a short while of a "trial-and-error" testing with the multi-dimensional clustering algorithm and achieving some experience about how well which features are in a combination with others, I decided to start a systematic searching process beginning with four-tuple combinations. In the followings, I will mention some of the general observations[41] we made;

- not always all of the good one-dimensional features were represented within the best feature combinations,
- good one-dimensional features with the same detection rate did not provide the same results within coequal combinations,
- some poor or average individual features turned out to be the best features in a combination with others,
- by repeating some features in a combination, we obtained a few new good combinations,
- good feature combinations always gave us better results than any of the features individually and
- the quality of the feature tuple does not depend on the order of the features within the tuple.

In the following tables, you see an example for using the random search method for polydat_3 ('m=2' and 'm=5') for four-tuple combinations.

[41] See also chapter 4.3.

feature number = { 1, 4, 3, 9, 22, 29, 30, 36, 37, 39, 450, 457, 458, 460]
condition: if(((nn>=80) & (ww>=80)) | ((nn>=86) | (ww>=86)))

table 1

feature positions				right detection non-ok	dcp-ok
5	1	7	4	86	78
1	7	3	6	88	72
4	8	5	2	86	76
5	6	8	4	86	68
8	3	4	5	86	72
6	8	13	5	86	68
4	1	6	3	88	70
2	3	6	1	86	74
1	8	5	3	86	72
6	12	13	8	86	68
8	1	4	6	86	70
8	7	6	1	86	70
1	8	5	6	86	70
6	3	7	1	88	72
2	6	10	1	86	68
6	10	2	7	86	68
1	3	6	5	88	70
6	7	3	1	88	72
2	6	4	1	86	72
7	5	1	4	86	78
5	8	1	4	86	70
8	5	13	3	86	72
3	8	6	14	88	70
3	7	4	2	86	78
8	7	1	6	86	70
3	1	6	5	88	70
5	4	8	2	86	76

feature positions				right detection non-ok	dcp-ok
6	4	8	5	86	68
2	4	10	6	86	68
8	4	1	5	86	70
10	8	2	1	86	72
7	9	3	1	82	80
8	1	6	14	86	70
5	4	2	8	86	76
1	7	8	6	86	70
1	4	8	10	86	72
2	12	8	1	86	76
1	2	4	8	86	76
8	1	2	4	86	76
7	3	4	2	86	78
4	1	6	8	86	70
3	6	1	4	88	70
8	1	5	10	86	72
1	8	2	4	86	76
8	4	13	1	86	70
1	10	2	6	86	68
1	6	3	5	88	70
1	5	8	3	86	72
3	8	2	6	86	72
1	6	3	14	88	70
5	1	8	2	86	76
1	4	6	10	86	68
2	5	4	8	86	76
2	6	10	1	86	68

...

feature number = {1, 4, 3, 8, 9, 18, 22, 29, 30, 36, 37, 39, 81, 457}
condition: if(((nn>=80) & (ww>=80)) | ((nn>=86) & (ww>=78)))

table 2

feature positions				right detection non-ok	dcp-ok
2	3	9	14	86	78
3	5	2	9	86	78
9	3	2	4	86	78
9	1	4	5	86	78
1	4	13	9	86	78
9	4	3	2	86	78
7	1	4	9	86	78
5	7	9	1	86	78
2	9	3	7	86	78

feature positions				right detection non-ok	dcp-ok
7	1	13	9	86	78
9	3	13	2	86	78
1	9	5	4	86	78
7	3	2	9	86	78
7	9	4	1	86	78
4	2	3	9	86	78
1	7	9	4	86	78
9	1	13	5	86	78

Fig. 24.I: Feature combinations by 'random search' - polydat_3, 'm=2'

feature number = {1, 4, 3, 7, 8, 9, 22, 30, 36, 37, 81, 308, 457, 459}

condition: if(((nn>=80) & (ww>=80)) | ((nn>=86) & (ww>=78)))

table 3

feature positions				right detection non-ok	right detection dcp-ok
8	7	6	1	86	78
7	8	1	5	86	78
3	2	8	6	86	78
3	8	5	2	86	78
1	3	10	8	82	80
3	8	2	6	86	78
3	2	13	8	86	78
2	8	5	3	86	78
1	6	5	8	86	78
5	8	3	2	86	78
1	8	13	5	86	78
6	1	8	7	86	78
2	5	8	3	86	78
5	2	3	8	86	78
3	8	6	2	86	78
3	7	2	8	86	78
2	8	5	3	86	78
7	6	1	8	86	78
3	5	2	8	86	78
8	5	6	1	86	78
7	2	3	8	86	78
8	5	6	1	86	78
7	8	2	3	86	78
7	8	6	1	86	78
8	1	7	6	86	78
1	8	5	6	86	78
1	7	6	8	86	78
5	8	1	6	86	78
6	1	5	8	86	78
7	8	5	1	86	78
8	7	2	3	86	78
8	2	3	7	86	78
6	5	1	8	86	78
1	8	7	6	86	78
6	7	8	1	86	78
1	6	13	8	86	78
6	8	13	1	86	78
8	7	1	6	86	78
5	1	7	8	86	78
2	6	8	3	86	78
3	2	8	7	86	78
1	6	8	5	86	78
2	5	8	3	86	78
8	1	5	7	86	78
2	5	3	8	86	78

feature positions				right detection non-ok	right detection dcp-ok
1	8	10	3	82	80
1	7	8	14	86	78
6	7	1	8	86	78
10	8	1	3	82	80
5	3	2	8	86	78
7	1	6	8	86	78
6	2	8	3	86	78
7	6	8	1	86	78
8	5	3	2	86	78
1	8	6	14	86	78
3	5	8	2	86	78
7	3	8	2	86	78
8	5	2	3	86	78
8	6	7	1	86	78
8	1	5	7	86	78
1	6	13	8	86	78
7	3	8	2	86	78
6	8	1	5	86	78
5	1	8	7	86	78
1	7	13	8	86	78
1	8	5	6	86	78
8	3	2	7	86	78
6	2	8	3	86	78
8	2	3	5	86	78
6	8	2	3	86	78
8	3	6	2	86	78
2	8	3	5	86	78
2	6	3	8	86	78
5	8	1	7	86	78
8	5	13	1	86	78
1	3	8	10	82	80
7	3	2	8	86	78
3	2	5	8	86	78
3	10	1	8	82	80
8	3	1	10	82	80
8	1	5	6	86	78
3	2	13	8	86	78
1	7	8	6	86	78
3	2	5	8	86	78
2	3	8	6	86	78
5	8	13	1	86	78
8	3	13	2	86	78
8	3	5	2	86	78
8	2	3	5	86	78
6	8	2	3	86	78

Fig. 24.I: Continued

feature number = {1, 4, 3, 8, 9, <u>21</u>, 22, 30, <u>35</u>, 36, 81, <u>198</u>, 457, 459}

condition: if (((nn>=80)&(ww>=80)) | ((nn>=86) & (ww>=78)))

table 3

feature positions				right detection non-ok	right detection dcp-ok
1	8	5	4	86	78
7	1	8	14	86	78
7	1	8	5	86	78
4	2	8	3	86	78
3	2	8	5	86	78
8	1	4	7	86	78
3	4	2	8	86	78
8	2	3	7	86	78
5	8	13	1	86	78
1	4	13	8	86	78

feature number = {1, 4, 3, 8, 9, 22, 30, 35, <u>51</u>, <u>111</u>, <u>210</u>, <u>455</u>, 457, 459}

condition: if (((nn>=80)&(ww>=80)) | ((nn>=86) & (ww>=<u>79</u>)))

table 4

feature positions				right detection non-ok	right detection dcp-ok
7	5	10	6	80	80
6	4	7	10	80	80
7	4	10	5	80	80

Fig. 24.I: Continued

feature number = {1, 3, 4, 8, 9, 22, 30, 37, 81, 111, 452, 450, 459, 460}

condition: if (((nn>=80) & (ww>=80)) | ((nn>=86) & (ww>=79)))

table 1

feature positions				right detection non-ok	right detection dcp-ok
1	12	5	9	86	80
5	10	2	8	80	80
6	12	1	9	86	80
1	9	7	5	86	80
10	9	6	7	84	82
7	10	9	6	84	82
2	1	5	8	80	80
10	8	7	6	80	82
7	4	9	1	86	80
1	8	2	4	80	80
1	7	5	9	86	80
8	3	1	10	80	80
5	8	1	2	80	80
8	2	4	10	80	80
5	12	7	3	82	80

feature positions				right detection non-ok	right detection dcp-ok
8	5	1	2	80	80
8	5	2	1	80	80
1	6	2	8	80	80
10	6	2	8	80	80
1	9	7	14	86	80
1	9	8	2	80	80
5	12	9	8	80	80
3	10	8	1	80	80
8	12	1	3	80	80
1	4	8	2	80	80
1	12	13	9	86	80
10	8	2	9	80	80
7	9	6	1	86	80
9	5	7	10	84	82
2	1	4	8	80	80

Fig. 24.II: Feature combinations by 'random search' - polydat_3, 'm=5'

feature number = {1, 4, 8, 9, 22, 30, 32, 37, 67, 81, 452, 450, 459, 457}
condition: if(((nn>=81) & (ww>=81)) | ((nn>=86) & (ww>=79)))

table 2

feature positions				**right detection** non-ok	dcp-ok
1	6	4	10	86	80
6	4	1	10	86	80
1	12	3	10	86	80
1	12	13	14	86	80
3	6	1	10	86	80
6	10	5	1	86	80
4	6	10	1	86	80
10	3	1	6	86	80
3	12	10	1	86	80
1	12	10	5	86	80
10	12	1	14	86	80

Fig. 24.II: Continued

After running similar simulations for different *m*'s with randomly chosen features from the pool of the aforementioned five[42] groups, I started a sequence of pseudo-exhaustive searches with those features from which we received good results by random search.
For this sequence of simulations the parameter *m* was set equal to 5. We started with four-tuple combinations out of a pool of 14 features (4/14). We then gradually increased the number of the features - within the tuple and the pool - up to 8/22. To run the simulation with this final setting, we needed a computation time of several weeks.

In the following figures, you see an example for one of the best 4-tuple results we obtained for the polydat_3:

4-tuple combination:	81 & 111 & 450 & 452[43].
dimension:	polygraph session.
correct detection rate:	84% for non-deceptive and 86% for deceptive files.
dimension:	polygraph examination[44] - containing 1 to 4 sessions.
correct detection rate:	89% for non-deceptive and 94% for deceptive files.
dimension:	polygraph examinations with more than two sessions.
detection rate:	100%.

[42]See Fig. 8 for four of them and page 25 for the additional fifth one.
[43]For information about the exact meaning of these feature *numbers*, see Fig.41.
[44]See "Evaluation strategy" in chapter 3.1.3.4.

Uik	defuzzification per session	test	
0.2727	0		
0.4680	0		
0.4404	0		
----------------------------		0	
0.5774	1.0000		
0.3208	0		
0.4075	0		
----------------------------		0	
0.6157	1.0000		
0.5416	1.0000		
----------------------------		1	*misclustered*
0.4095	0		
0.4480	0		
0.4862	0		
----------------------------		0	
0.4722	0		
0.4755	0		
0.5046	1.0000		
----------------------------		0	
0.4387	0		
0.4459	0		
0.4346	0		
----------------------------		0	
0.4005	0		
----------------------------		0	
0.4351	0		
0.4251	0		
0.3723	0		
----------------------------		0	
0.4505	0		
0.4414	0		
0.3218	0		
----------------------------		0	
0.4428	0		
0.4474	0		
0.5997	1.0000		
----------------------------		0	
0.3764	0		
0.3709	0		
0.3383	0		
----------------------------		0	
0.4668	0		
0.4843	0		
0.4515	0		
----------------------------		0	
0.3964	0		
0.5232	1.0000		
0.4085	0		
----------------------------		0	
0.3915	0		
0.4425	0		
0.3860	0		
----------------------------		0	
0.4200	0		
0.4443	0		
0.4315	0		
----------------------------		0	
0.4974	0		
0.3980	0		
0.3964	0		
----------------------------		0	
0.5863	1.0000		
----------------------------		1	*misclustered*
0.3786	0		
0.5783	1.0000		
0.4377	0		
0.3527	0		
----------------------------		0	

non-deceptive files
polydat_3
m=5

Fig.25: Defuzzified results for [81-111-450-452] feature combination

Uik	defuzzification per session	test
0.6374	1.0000	
0.5389	1.0000	
0.5094	1.0000	
----------------------------		1
0.5696	1.0000	
0.4185	0	
0.5057	1.0000	
----------------------------		1
0.5508	1.0000	
0.5237	1.0000	
----------------------------		1
0.5533	1.0000	
0.5878	1.0000	
0.5941	1.0000	
----------------------------		1
0.4533	0	
0.5383	1.0000	
0.5316	1.0000	
----------------------------		1
0.5452	1.0000	
0.5266	1.0000	
0.3128	0	
----------------------------		1
0.5068	1.0000	
0.5735	1.0000	
0.6276	1.0000	
----------------------------		1
0.5504	1.0000	
0.5706	1.0000	
0.5542	1.0000	
----------------------------		1

0.5555	1.0000		
0.5692	1.0000		
0.5650	1.0000		
----------------------------		1	
0.4418	0		
0.6468	1.0000		
0.5009	1.0000		
----------------------------		1	
0.5593	1.0000		
0.5596	1.0000		
0.4109	0		
----------------------------		1	
0.6002	1.0000		
0.5550	1.0000		
0.5148	1.0000		
----------------------------		1	
0.5964	1.0000		
0.6112	1.0000		
0.6224	1.0000		
----------------------------		1	
0.7130	1.0000		
0.5834	1.0000		
0.5844	1.0000		
----------------------------		1	
0.5472	1.0000		
0.5758	1.0000		
0.5924	1.0000		
----------------------------		1	
0.5879	1.0000		
0.6284	1.0000		
0.6078	1.0000		
----------------------------		1	
0.3902	0		
0.5399	1.0000		
0.4636	0		
----------------------------		0	*misclustered*

deceptive files
polydat_3
m=5

Fig.25: Continued

4.1.2.2. Results of the genetic method:

Simultaneously to the aforementioned sequence of searches, I started with a compromise between the random and the pseudo-exhaustive search method; i.e. the genetic alternative. I decided to use this method in two different ways:

1. In order to increase the number of potentially good features in the pool, I initialized the genetic code with up to 50 features from which (in different simulations) 4-, 6-, 8-tuple combinations were made.

2. In order to accelerate the search, but process the data more exhaustively, I decided to use the genetic code only for the best features from random and pseudo-exhaustive simulations and narrow the feature pool to these 30 selected features. In this simulation, 15-tuple combinations were made.

Recall that having 30 or 50 features in the pool makes a big computation difference. For example, choosing exhaustively 8-tuples out of 50 or 30 features makes a difference of following number of computations:

$$\binom{50}{8}-\binom{30}{8}=\frac{50!}{8!(50-8)!}-\frac{30!}{8!(30-8)!}\approx 5\cdot 10^{8}$$

In the first part of the genetic search - as expected - we had similar problems as scientists have with the theory of evolution as the cause of our being[45]. The only way we could get the following good results was the continuous manipulating of the evolution process - by changing parameters (like mutation rate), features (=genes) and feature numbers (=population size and also number of genes in one chromosome), or by starting again if the simulation began with a very low detection rate (=average fitness). In spite of these manipulations the first version of the genetic search took a simulation time of over two months of continuous computation. Without the constant *controlling* process over this genetic system the *evolution* (by chance as it is its nature) could have hardly provided any appropriate improvement[46]. As a result we obtained 12 (see Fig.26) 8-tuples combination

[45]Further discussion about "evolution vs. creation" would break up the limitations of this project; For interested readers I recommend the following references: [Morris1987] [Johnson1991].

[46]For example, one of the *uncontrolled* simulation for polydat_1 was stopped after 561 generations providing no particular results.

with an average of 85% correct detection rate for polydat_3 similar to the results of the 4-tuple combination mentioned in chapter 4.1.2.1. We also obtained 3 outstanding (86% correct detection rate) individuals within three different generations (population size of 200 to 300, total number of generation 1000, polydat_3).

feature numbers of the best 8-tuple combinations	correct detection rate ndcp	dcp
8 , 30 , 81 , 81 , 111 , 363 , 458 , 482	84	86
9 , 37 , 81 , 111 , 111 , 449 , 458 , 460	84	86
9 , 37 , 111 , 111 , 449 , 457 , 457 , 482	84	86
9 , 37 , 111 , 111 , 358 , 449 , 457 , 458	84	86
9 , 37 , 111 , 111 , 235 , 449 , 457 , 460	84	86
37 , 79 , 111 , 111 , 197 , 358 , 449 , 457	84	86
37 , 111 , 111 , 197 , 449 , 457 , 460 , 460	84	86
37 , 111 , 111 , 111 , 235 , 358 , 457 , 458	84	86
37 , 111 , 111 , 235 , 235 , 449 , 453 , 457	84	86
37 , 111 , 111 , 197 , 358 , 361 , 458 , 460	84	86
37 , 81 , 111 , 235 , 235 , 363 , 450 , 453	86	84
37 , 81 , 111 , 235 , 235 , 359 , 450 , 453	86	84
37 , 79 , 111 , 111 , 197 , 235 , 449 , 457	86	86
37 , 111 , 111 , 235 , 235 , 453 , 457 , 460	86	86
37 , 111 , 111 , 197 , 235 , 452 , 457 , 460	86	86

ndcp: non-deceptive files
dcp: deceptive files
data: polydat_3

Fig.26: Results of the first version of the genetic search

Concerning the *defuzzified* results, all the combinations with 85% correct detection rate show similar structure as depicted in Fig.25. The three best 8-tuple combinations (86% correct detection rate) cluster the data exactly in the same groups as shown in the following figure.

Uik **defuzzification per**
session **test**

0.4143 0
0.4780 0
0.4583 0
---------------------------- 0

0.5269 1.0000
0.4035 0
0.4035 0
---------------------------- 0

0.5601 1.0000
0.5412 1.0000
---------------------------- 1 *misclustered*

0.4391 0
0.4465 0
0.4833 0
---------------------------- 0

0.4669 0
0.4679 0
0.5058 1.0000
---------------------------- 0

0.4401 0
0.4392 0
0.4481 0
---------------------------- 0

0.4114 0
---------------------------- 0

0.4405 0
0.4212 0
0.4664 0
---------------------------- 0

0.4523 0
0.4488 0
0.3645 0
---------------------------- 0

0.4565 0
0.4853 0
0.5849 1.0000
---------------------------- 0

0.4441 0
0.4471 0
0.3506 0
---------------------------- 0

0.4983 0
0.4872 0
0.4938 0
---------------------------- 0

0.4008 0
0.4962 0
0.4058 0
---------------------------- 0

0.4268 0
0.4740 0
0.4050 0
---------------------------- 0

0.4475 0
0.4517 0
0.4440 0
---------------------------- 0

0.5692 1.0000
0.4432 0
0.4118 0
---------------------------- 0

0.4289 0
---------------------------- 0 *compare to Fig.25*

0.4271 0
0.5548 1.0000
0.4696 0
0.4135 0
---------------------------- 0

non-deceptive files
polydat_3
m=5

Fig.27: Defuzzified results for [37-111-111-197-235-452-457-460] feature combination

Uik	defuzzification per session	test	
0.5842	1.0000		
0.5511	1.0000		
0.5197	1.0000		
		1	
0.5665	1.0000		
0.5483	1.0000		
0.6586	1.0000		
		1	
0.5227	1.0000		
0.5169	1.0000		
		1	
0.5519	1.0000		
0.5727	1.0000		
0.5747	1.0000		
		1	
0.5411	1.0000		
0.5224	1.0000		
0.6020	1.0000		
		1	
0.4308	0		
0.4916	0		
0.4801	0		
		0	*misclustered*
0.5044	1.0000		
0.5686	1.0000		
0.5830	1.0000		
		1	
0.5488	1.0000		
0.5460	1.0000		
0.5413	1.0000		
		1	
0.5446	1.0000		
0.5495	1.0000		
0.5615	1.0000		
		1	
0.5345	1.0000		
0.5666	1.0000		
0.5370	1.0000		
		1	
0.5539	1.0000		
0.5565	1.0000		
0.4388	0		
		1	
0.5817	1.0000		
0.5042	1.0000		
0.4946	0		
		1	
0.5706	1.0000		
0.5990	1.0000		
0.6133	1.0000		
		1	
0.6386	1.0000		
0.5674	1.0000		
0.5576	1.0000		
		1	
0.5457	1.0000		
0.5646	1.0000		
0.5482	1.0000		
		1	
0.5096	1.0000		
0.5954	1.0000		
0.6347	1.0000		
		1	
0.4532	0		
0.4323	0		
0.5457	1.0000		
		1	*compare to Fig.25*

deceptive files
polydat_3
m=5

Fig.27: Continued

The followings are the clustering results of the best 8-tuple combinations for polydat_3:

dimension:	polygraph session[47].
correct detection rate:	86% for both non-deceptive and deceptive files.
dimension:	polygraph examination - containing 1 to 4 sessions.
correct detection rate:	94% for both non-deceptive and deceptive files.
dimension:	polygraph examinations with more than two sessions
detection rate:	97%.

In the second part of the genetic search as we fed the evolution process with the best features, we obtained after about 3 weeks of continuous simulation the following results:

twelve 15-tuple combinations: (the features in each tuple are ordered vertically)

37	11	8	8	37	30	11	30	11	11	11
111	11	11	37	81	32	30	32	30	30	30
111	36	37	50	81	32	32	39	32	32	32
197	36	111	79	81	32	39	81	39	39	39
358	37	111	111	81	36	81	81	81	79	81
358	37	197	111	197	37	81	81	81	81	81
361	67	235	235	235	39	81	111	81	81	81
361	81	358	235	358	50	111	197	111	81	111
449	197	359	358	359	67	197	235	197	111	197
457	235	359	452	450	79	235	235	235	197	235
458	457	363	453	450	359	235	358	235	235	235
458	458	363	478	453	449	358	358	358	235	358
478	482	452	478	458	449	359	450	358	358	359
478	482	478	478	478	478	450	478	450	359	450
482	482	482	482	478	478	482	482	482	450	478

correct detection rates (in %):

84	84	84	84	84	84	84	84	84	84	84	**:non-deceptive files**
86	86	86	86	86	86	86	86	86	86	86	**:deceptive files**

polydat_3, m=5

Fig.28: Results of the second version of the genetic search

[47] See "Evaluation strategy" in chapter 3.1.3.4.

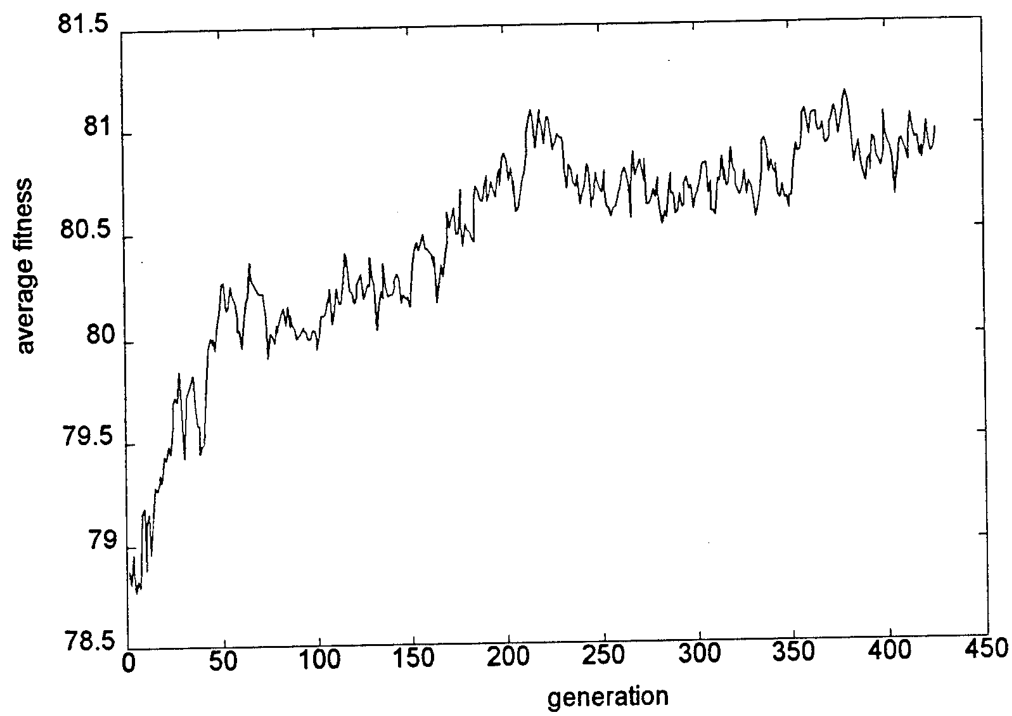

Fig.29: Average fitness of each generation provided by the second version of the genetic search

As you see in this figure, the average fitness (from all the chromosomes within a generation) increases over the period of time. It then approaches a local asymptote which represents a local error minimum. By increasing the mutation rate after the 150th generation, we could avoid being stuck in that local minimum for further development. This higher mutation rate helped the evolution process getting a 1% better average fitness per generation for the rest of the simulation.

Our hope for this simulation was to get *outstanding* chromosomes with a very high fitness simultaneously to the increasing process of the *average* fitness per generation. However, the outstanding chromosomes appeared unsystematically in different generations and not at the end. In fact, most of them[49] belong to the first part of this evolution.

[48]See the begining of this chapter for more details.
[49]See Fig.28 for the best feature combinations.

4.1.2.3. Final results of FCM- A comparison between all three polydat_i's:

All the aforementioned results belong to the data set polydat_3, and all the three methods, (1) previous researches using the fuzzy K-nearest neighbor (KNN) classifier, (2) the LMS fuzzy adaptive filter and also (3) the fuzzy-c-means algorithm show that the data structure within the polydat_3 is better to cluster or classify than the other two sets.

As it is the nature of a *clustering* versus a *classifying* method, I did not set the highest priority on finding the *same* best features for all three polydat_i's, but for each of them individually. After finding those best combinations, I then compared the results and tested the consistency of the features (see Fig. 33, 34, 35).

Using either *sessions* or *examinations*[50] as the counting dimension the best results for each polydat_i individually are shown in the following figures.

data	average correct detection rate
polydat_1	81%
polydat_2	79%
polydat_3	86%

Fig.30: Clustering results using individual features (using *sessions* as the counting dimension)

data	average correct detection rate
polydat_1	91%
polydat_2	82%
polydat_3	94%

Fig.31: Clustering results using individual features (using *examinations* as the counting dimension)

[50] See "Evaluation strategy" in chapter 3.1.3.4.

data	average correct detection rate
polydat_1	93%
polydat_2	87%
polydat_3	97%

Fig.32: Clustering results using individual features (counting only those *examinations* with more than two sessions)

In the following figures, a comparison between the three polydat_i's were made using the best feature combination for one of the polydat_i's at a time and testing it for the other two ones. As you will see, the best result[51] - while taking the *same* features for each polydat_i - is 79.7% for the feature combination[52] [9, 30, 81, 197, 478, 111], and in average 79.3%.

feature tuple	polydat_i i=3	i=2	i=1
37, 79, 111, 111, 197, 235, 449, 457	86%	77%	75%
37, 111, 111, 197, 235, 452, 457, 460	86%	77%	75%
37, 111, 111, 235, 235, 453, 457, 460	86%	77%	74%
30, 81, 81, 111, 197, 458	85%	79%	73%
9, 30, 81, 111, 197, 458	85%	79%	73%
8, 37, 50, 79, 111, 111, 235, 235, ... 358, 452, 453, 478, 478, 478, 482	85%	76%	76%

Fig.33: Comparison #1 (dimension: sessions) (taking some of the best *polydat_3* feature tuples and testing it for the others)

For the exact *labels* of this feature *numbers* see appendix, Fig.42.

[51]With polygraph *sessions* as the counting dimension.
[52]See Fig.35, "Comparison #3".

feature tuple	polydat_i i=1	i=2	i=3
9, 30, 30, 39, 235, 450	80%	75%	81%
30, 30, 39, 50, 235, 450	80%	75%	81%
30, 30, 39, 81, 235, 450	80%	75%	81%
30, 30, 39, 197, 235, 450	81%	74%	82%
30, 30, 39, 235, 363, 450	81%	75%	81%
30, 30, 39, 235, 358, 450	80%	76%	81%
30, 30, 39, 235, 450, 458	80%	75%	81%
30, 30, 39, 235, 482, 450	80%	75%	81%
30, 30, 39, 235, 361, 450	80%	75%	81%
30, 30, 39, 235, 359, 450	80%	75%	81%
30, 30, 39, 235, 450, 457	80%	75%	81%
30, 39, 235, 363, 450, 482	80%	72%	83%
30, 39, 235, 363, 450, 478	80%	71%	83%

Fig.34: Comparison #2 (dimension: sessions)

(taking some of the best *polydat_1* feature tuples and testing it for the others)

feature tuple	polydat_i		
	i=2	i=1	i=3
9, 30, 81, 197, 478, 111	79%	75%	85%
9, 30, 50, 81, 197, 111	79%	74%	85%
9, 30, 81, 358, 197, 111	79%	74%	85%
9, 30, 81, 359, 197, 111	79%	74%	85%
9, 30, 81, 197, 457, 111	79%	74%	85%
30, 81, 105, 111, 197, 358	79%	74%	84%
30, 81, 105, 111, 197, 359	79%	74%	84%
30, 81, 105, 111, 197, 457	79%	74%	85%
30, 81, 105, 111, 197, 459	79%	74%	84%
30, 81, 111, 197, 358, 359	79%	74%	85%
30, 81, 111, 197, 358, 456	79%	74%	85%
30, 81, 111, 197, 358, 457	79%	74%	85%
30, 81, 111, 197, 358, 459	79%	74%	85%
30, 81, 111, 197, 359, 456	79%	74%	85%
30, 81, 111, 197, 359, 457	79%	74%	85%
30, 81, 111, 197, 359, 459	79%	74%	85%
30, 81, 111, 197, 456, 457	79%	73%	85%
30, 81, 111, 197, 456, 459	79%	74%	85%
30, 81, 111, 197, 457, 459	79%	74%	85%
30, 105, 111, 197, 359, 459	79%	74%	84%
30, 105, 111, 197, 456, 459	79%	74%	84%
30, 105, 111, 197, 457, 459	79%	74%	85%
30, 105, 111, 197, 456, 457	78%	74%	85%
30, 111, 197, 358, 359, 459	78%	74%	85%
30, 111, 197, 358, 456, 459	78%	74%	85%
30, 111, 197, 358, 457, 459	78%	74%	85%
30, 111, 197, 456, 457, 459	78%	74%	85%

Fig.35: Comparison #3 (dimension: sessions)

(taking some of the best *polydat_2* feature tuples and testing it for the others)

4.2. LMS fuzzy adaptive filter

The first test we did, was to find the performance of the filter before any training. That is, we used the classifier as a conventional fuzzy logic system designed solely based on the four linguistic rules mentioned above. The results are listed in the following table:

polydat_i	correct detection rate in non-deceptive files	deceptive files	average
i=1	70%	72%	71%
i=2	70%	76%	73%
i=3	70%	88%	79%

Fig.36: Results based solely on 4 aforementioned linguistic rules without any training

Note that the percentage of correct recognition for non-deceptive subjects are the same for polydat_1, polydat_2, and polydat_3, because they are all the same data[53]. Also note that the results are best for polydat_3, as it was for KNN and FCM. This may be partially due to polydat_3's good performance in general, independent of the classifying schemes. We believe that it may also be a result of us setting up the linguistic rules by having observed polydat_3.

However, the outcomes for polydat_1 and polydat_2 are good enough such that one can be sure the linguistic rules are sufficiently general even for data that we did not examine.

As mentioned in chapter 3.2.3, we then tested the fuzzy LMS algorithm trained with twenty training data (ten deceptive and ten non-deceptive) and again with seventy training data (thirty-five deceptive and thirty-five non-deceptive) for the three sets of data, for a total of six tests. Twenty trials were performed for each test, and the system was initialized with the linguistic rules before each trial. The training data were randomly chosen for each trial, and the rest of the available data in each set were for testing.

[53]See polygraph files on chapter 6.2.

We computed the percentage of correct recognition of testing data for each trial, averaging the performance for deceptive and non-deceptive subjects. The recognition rate of those twenty trials are averaged, rounded to two digits, and reported in the following table. The sample standard deviations are also shown.

	correct detection rate	
polydat_i	**version #1**	**version #2**
i=1	75% (6%)	73% (2%)
i=2	74% (7%)	73% (3%)
i=3	78% (6%)	79% (2%)

version #1: *70 training & 30 testing sessions*
version #2: *20 training & 80 testing sessions*
(standard deviation in parentheses)

Fig.37: Average percentage of correct detection rate for twenty trials of each test

As may be expected, the recognition rate improves in general when training data is used, as compared to the results of the untrained system. Also, the recognition rate is typically higher when the system is trained with more data. The difference, however, is not dramatic. The use of training data offers small incremental improvements. The one exception would be for data set polydat_3. Here more training data seems to lower the performance. The effect is probably due to the fact that the initialization of the reasoning rules were based on our examination of polydat_3, which covered all 100 data. Yet the training algorithm was to learn only a subset of that, so it was handicapped compared to human reasoning.

Human reasoning may also be better in this case because the training algorithm only attempts to optimize the system in the least mean square sense, slightly different than our ultimate goal of maximizing recognition rate. At any rate, when the standard deviation is taken into account, the difference in recognition rate becomes insignificant.

Another noticeable difference between the results using different amounts of training samples is the value of the sample standard deviation. A large number of testing data leads to a small standard deviation. Conversely, a small amount of testing data leads to a large standard deviation. This confirms what we intuitively know; the average percentage of correct recognition is more accurate when a large amount of testing data is available.

The above observations illustrate a practical issue in using many adaptive and learning algorithms, that of partitioning a limited amount of data into training and testing sets. For most algorithms, too much data in training and little in testing leaves little assurance about the performance of the system. On the other hand, too much data in testing and little in training assures mediocre performance from the system.

More data for both training and testing would help, but many times that may not be available. Fuzzy logic systems mitigate this problem by exploiting linguistic information. Unlike neural networks and many statistical techniques, which are *completely* dependent on numerical data, this fuzzy LMS algorithm uses numerical data mainly to optimize a good fuzzy system. The above results show that, given good initialization of the reasoning rules, the system can perform well even with little or no training data. This robustness is one of the many advantages of fuzzy logic.

4.3. Other observations:

During this project, aside from the results and conclusions we were looking for, we also obtained several side results. In this passage, I will mention some of the interesting observations we made.

1. As mentioned before, the fuzzy-c-means (FCM) algorithm is initialized by random chosen membership values which will be modified and optimized during the iterative process. Thus, FCM algorithm is *almost* independent of the initial membership values. During our testing process, we noticed that the FCM algorithm is not *absolutely* independent of the initial values. Thus, it is possible that

- the algorithm may run into different local minima or
- because of its unsupervised nature, the algorithm may switch the clusters, i.e. if - depending on our interpretation - the first cluster represents the non-deceptive and the second one the deceptive files, it might be the opposite while using other initial random values.

To avoid any misinterpretations, I decided to create two sets of random membership values (for c=2 and c=3) and save them as fixed initialization values for any further simulations. In the following figure, '+' represents the non-deceptive, '*' the decptive files;

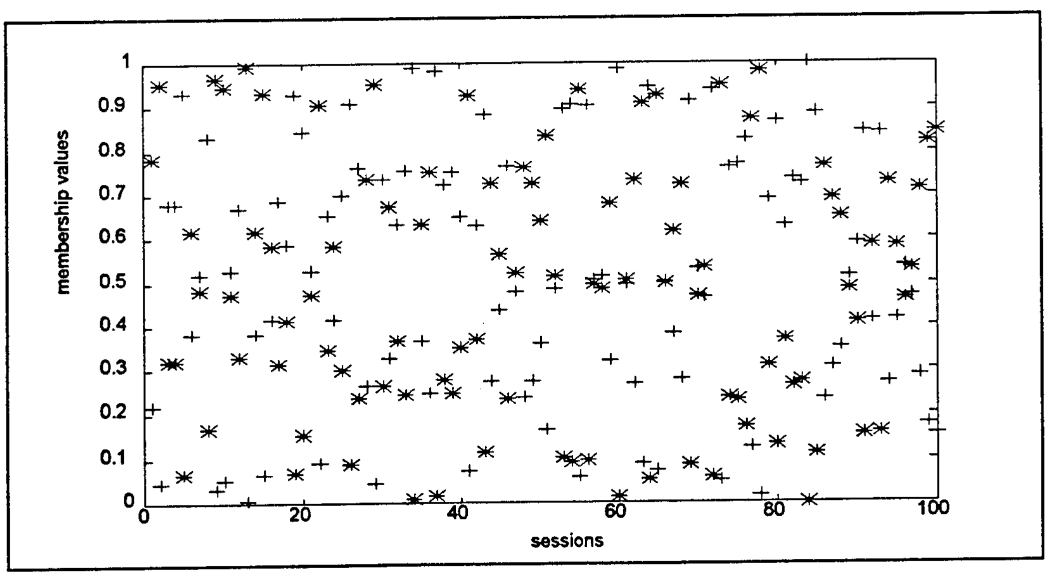

Fig.38: Fixed initial random membership values for c=2

2. "Outlier effect":

In the real world of using an automated polygraph system as suggested in this project, we have to keep in mind the existence of the outlier effect. This occurs, for instance, when a non-deceptive person (= membership value between zero and 0.5) becomes misclustered in a deceptive data space with a very high membership value close to one. In other words, if a normal non-deceptive person gets labeled as *very* deceptive, or vice-versa.

We noticed this phenomenon in both clustering and classifying algorithms[54]. We also noticed that by making the system "fuzzier" - e.g. higher m or/and c for FCM - as expected, the outlier effect can be reduced, but not eliminated though.

3. "Performance limitations":

There seem to be a limit in recognition rate using the features available by both fuzzy algorithms used in this project and also by fuzzy k-nearest neighbor algorithm used in previous works [Layeghi1993,1] [Dastmalchi1993] for all the available polydat_i's. There may also be psychophysiological limitation on the recognition rate. However, polydat_3 provided, independent of all the three algorithms, the best results compared to the other two polydat_i's.

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[54]See also *"Epilogue"*.

4.3. A COMPARISON

BETWEEN THE THREE FUZZY ALGORTHMS USED IN THIS AND THE PREVIOUS PROJECT

(FUZZY-C-MEANS, LMS FUZZY ADAPTIVE FILTER AND FUZZY K-NEAREST NEIGHBOR)

The fuzzy LMS system is unique in its application of linguistic knowledge. As mentioned earlier, the use of linguistic knowledge ensures the robustness of the fuzzy system. The use of linguistic information also ameliorates the problem of not having enough reliable numerical data. Unlike classification schemes such as the K-Nearest Neighbor, the fuzzy LMS algorithm is not entirely dependent on numerical data.

When applied to pattern recognition, fuzzy *logic* systems can be set up to perform like KNN systems. In KNN systems, numerical data of known class patterns are set up to estimate the probability density distribution of the classes. The probabilities of new data points belonging to the different classes are then computed based on such distribution. Data points around known class samples are then classified into the same class with a higher probability. The fuzzy-KNN algorithm modifies the classical KNN algorithm by taking into account the distance between the data point and the known class patterns when estimating the probability. Conceptually this is similar to setting up clusters around all known class samples and calculating the degree of belonging of new data points in the different types of clusters. Other than the exact mathematical equations, that description fits a fuzzy adaptive system where each rule corresponds to a known class pattern and the size of the clusters is the same for all rules.

However, fuzzy adaptive systems give up some of the nice theoretical understandings of the KNN systems but gain some practical advantages. The number of rules required are usually much smaller than the number of known samples. Fuzzy *logic* can usually exploit that to reduce system complexity.

Furthermore, the system complexity for a fuzzy adaptive system stays the same even as new information are available. This is partly a result of the way this algorithm adapt continuously; new information are learned as old ones are forgotten. The fuzzy LMS learning technique is like backpropagation, a popular neural network training technique. However, the fuzzy LMS learning algorithm requires few epochs for training. In all our trials the maximum recognition rates for testing data peaked in less than thirty epochs. About 95% of them peaked in less than twenty epochs[55]. This is a few orders of magnitude less than most applications of backpropagation. In many cases the peaks occurred before any training; that is, the system uses only linguistic rules. Here the use of expert knowledge speeds up the training of the system.

The fuzzy-c-means algorithm, unlike fuzzy LMS, is an unsupervised clustering algorithm. Given a set of data, FCM looks for a (usually) predetermined number of clusters within the data points. It does not use any knowledge about the correct, or desired classification of any of the elements. The algorithm only minimizes an objective function, which is the sum of a function of the data points' membership values and the distances between the data points and the clusters' centers.

FCM operates like a black box; given some data, the algorithm automatically computes the results[56]. This presents the advantage that different sets of data using different features can be tested in a routine manner. FCM also presents a way to normalize the different dimensions of the data, just like the use of sigma in the fuzzy LMS algorithm. However, unlike fuzzy LMS, FCM does not present a method to find the optimal way for such normalization.

The fuzzy LMS algorithm, however, does pose some potential problems of its own. The use of expert knowledge, while a benefit in some senses, may not be always straightforward. For example, in our project we did not have any specific knowledge about the polygraphy itself. Whatever we learned, we learned by looking at numerical data. As we tried to find more complicated patterns, patterns involving three, four, or more features, the analysis became more difficult. Naturally one wishes to automate this process. If we do not rely on some learning procedures, however, rules cannot be automatically found for the fuzzy system. Much research also needs to be done to understand the fuzzy LMS algorithm's learning dynamics. While the same method, gradient descent, is used on both backpropagation and the fuzzy LMS algorithm, the general shapes of the error surface between the two are different. In backpropagation, all the parameters have the same range and lie in an uniform neural network structure. In the fuzzy LMS algorithm, the parameters can have different ranges and lie a fuzzy logic

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[55]However, we ran every trial to forty epochs to ensure that there is no "false" peak.
[56]Our job is basically to adjust the parameters.

structure that is not completely uniform. The effects of such differences on the shape of the error surface and the learning dynamic are unknown.

In the following, I will mention again some of the results we obtained by using different fuzzy clustering or classifying algorithms. Recall that also the searching strategies to find the best features -and feature combinations- were different for each of the aforementioned algorithms[57].

	polydat_i		
	i=1	i=2	i=3
fuzzy-c-means[58]	**91%**	82%	**94%**
fuzzy-c-means[59]	**93%**	87%	**97%**
fuzzy K-nearest-neighbor	86%	80%	**91%**
LMS fuzzy adaptive filter	81%	83%	83%
fuzzy-c-means[60]	81%	79%	86%

The results are rounded.

Fig.39: Comparison between different fuzzy algorithms used for polygraph classification in this and in the previous research

The results of our fuzzy LMS system, while impressive for such a simple set-up, are not comparable to the results of the same project using other systems. We believe that the recognition rate will increase for few percentage points by using the suggestions in chapter 5.1.

[57]See the following chapters 3.1.3.1, 3.1.3.2.1 - 4 for the searching strategies used for the FCM, chapter 3.2.1 for the visual inspection used for the LMS system, and chapter III.3.3. in [Layeghi1993,1] for the methods used for the KNN.

[58]FCM using *examinations* as the counting dimension (see chapter 4.1.2.3. and Fig.31).

[59]The same as above but counting those examinations with more than 2 sessions (see Fig.32).

[60]Since we took 35 out of 50 available non-deceptive *sessions* for training the LMS filter, it would be meaningless to evaluate this algorithm by *examinations* as the counting dimension. Yet, in order to make it comparable to the other algorithms, the results of the FCM with *sessions* as the counting dimension are also shown.

§5. FUTURE STEPS AND SUGGESTIONS

5.1. The algorithms:

As mentioned earlier in chapter 2.2.3. about the fuzzy-c-means algorithm, the performance of this clustering model is influenced by the choice of various parameters. In this project, I tried to find the optimum values of the majority of them. However, there are several other points which should be studied more comprehensively: They are

- the initial cluster centers,
- the order in which the samples are taken as input,
- the choice of distance measure,
- the termination criteria and
- the geometrical properties of the data.

Most imprtantly, more information about the geometrical arrangement of the data points and the appropriate choice of the norm could help us improve the clustering algorithm. There are several suggestions in [Bezdek1981] [Bezdek1992] [IIScorp1993] for a better understanding of the algorithm's dynamics and for making systematic decisions concerning different types of distance norms and elliptical cluster shapes.

For future studies, I highly recommend a deeper investigation of our clustering algorithm by setting c=3 and trying defuzzification thresholds other than 0.5.

In this project, we decided to systematically test the FCM algorithm with different values of *m* to find its optimum. For additional (and more theoretical) investigations, I suggest [Choe1992] as an introductory step. It may be also helpful to use different values of *m* for different *sessions* simultaneously, while looking for the most realistic clusters within the entire session *space*.

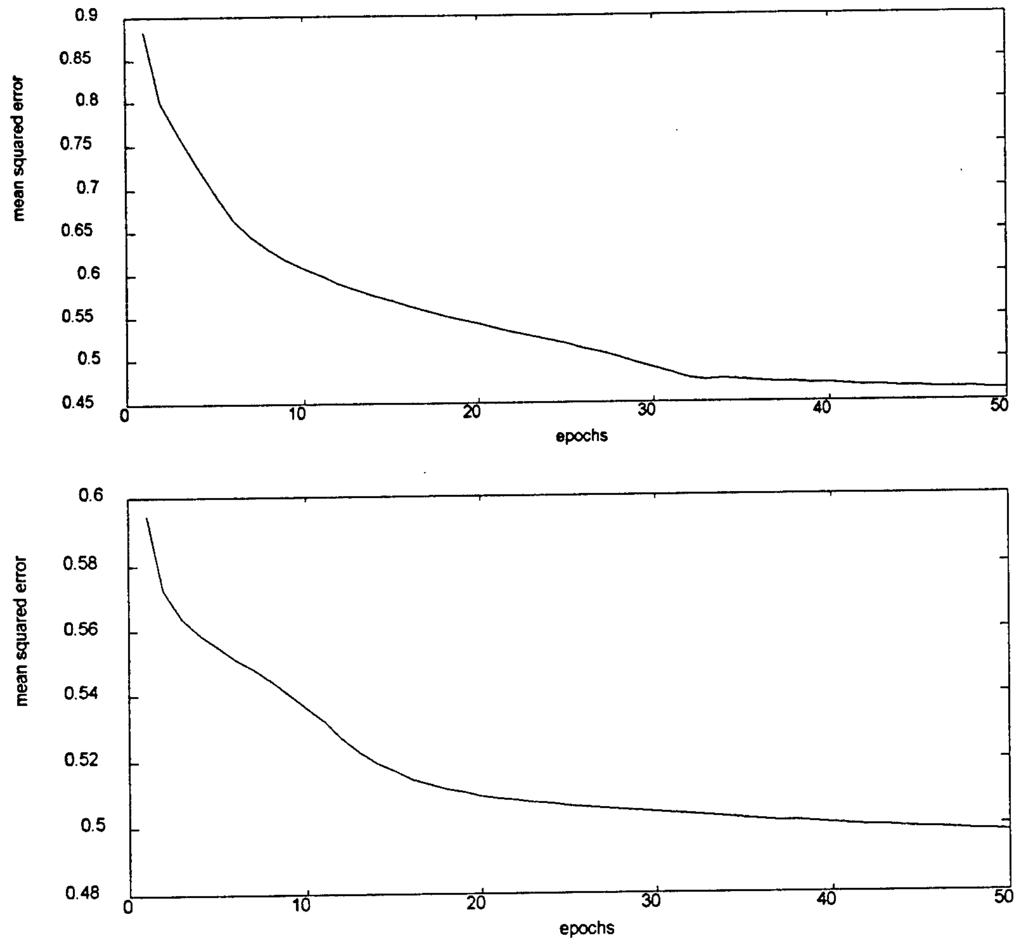
An exciting additional investigation would be a new polydat made up of the best clustered sessions of our three polydat_i's as a reference for any further clustering process. By doing this we could give the algorithm a better chance to cluster correctly even the critical sessions.

Concerning the LMS adaptive algorithm, one may investigate the effect of changing the learning factor; throughout our experiment it remained at 0.005. Upon observing the quickness of learning in our testing, we believe the learning factor can be decreased in the future.

We also believe that there should not be just one but at least three different learning factors: one for the σ's, one for the θ's, and one for the x_i's; because these three types of parameters lie in a very irregular parameter space, unlike that of backpropagation where all parameters lie in a more or less uniform parameter space.

For illustration, the three types of parameters comapred to one another have very different numerical ranges. Conceptually speaking, a parameter with a large range of movement should generally have a larger learning factor than one with a smaller range of movement. However, the gradient and the general shape of the error surface would also affect the value of the learning factors. It is possible that with a constant learning factor, a factor that is too large for one type of parameter - one that causes oscillation for that parameter - may be too small for another type of parameter and effects little change. That is, some parameters become more willing to adapt while others hesitate to change.

Setting up separate learning factors for the different types of parameters should eliminate this problem. However, choosing a learning factor is still a complex trial-and-error task, and having more learning factors to deal with requires more sophisticated understanding of the learning dynamics we possess. Plots of the mean squared error of two sets of randomly chosen training data suggest that there are noticeable points where the rate of decrease dramatically changes (see the following figure).



Two cases of the mean squared error of training data as the system "learns."

Fig.40: The influence of the learning factor

More rules and features should be added to improve this LMS system. As the complexity of the system grows, however, the design will depend more on the learning algorithm than on heuristic knowledge. This requires much more understanding of the learning dynamics. Preliminary testing with three features and eight rules shows little improvement in recognition rate. Obviously many additional studies need to be done in this case.

As mentioned in chapter "Setting Linguistic Rules", for future investigations one may also experiment with different decision thresholds for determining deception and nondeception. However, the benefit, if any, of this is not clear. One may also experiment with mapping the fuzzy output to a confidence value in addition to just a deception/nondeception decision. This may be more helpful in practical situations. One should also test the algorithm with random initializations; that is, without using any expert knowledge. It would be interesting to compare the training time, performance, and robustness of that system to the present one.

Fuzzy *logic* systems promote rapid development of robust, simple, and reliable systems. Our project validated that point. Some of the main problems with designing *traditional* fuzzy logic systems, however, are their dependence on heuristic information, their lack of design automation and their unproven ability to reach an optimal solution by linguistic rules alone. Our use of the LMS learning algorithm attempts to solve such problems. The learning algorithm did offer small, incremental improvements, but we believe that the learning algorithm has not yet been explored fully. A better understanding of the learning dynamics would offer more insight into improving the system.

In future works, one may also consider other strategies which use irrelevant questions, (see Fig.7). These questions could be easily exploited for normalizing the data and making it independent of individual charateristics of the tested subjects.

5.2. The polygraph examination:

As expected[61], and eventually proven[62], our clustering system can provide an up to 12% more correct detection rate by using the dependency between the polygraph sessions. Therefore, I recommend recording at least three - ideally five - test sessions with different a order of questions per each examinations. Thus, in cases where some sessions within an examination are clustered incorrectly, the algorithm can easily ignore the minority and find the right cluster according to the correctly clustered majority.

One may also consider other time frames, and emphasize those features which enabled us to cluster the data the best. It may also be helpful to mark the data of female and male subjects, or to consider them differently, since the ranges of the biophysical reactions are not in the same numerical spaces.

Ultimately, an automated polygraph system which uses the aforementioned strategies to distinguish between truth and deception should have a built-in feature extraction tool which can directly feed the needed data to the algorithm.

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[61]See chapter 3.1.3.4.
[62]See chapter 4.1.2.3.

§6. APPENDIX

Feat-ure	Chan-nel	Extraction Method	Combination Method
1	GSR	mean	ave(r) - ave(c)
2	GSR	mean	ave(r) + ave(c)
3	GSR	mean	max(r) - max(c)
4	GSR	mean	min(r) - min(c)
5	GSR	mean	max(r) - min(c)
6	GSR	mean	min(r) - max(c)
7	GSR	curve length	max(r) / max(c)
8	GSR	curve length	ave(r) - ave(c)
9	GSR	curve length	ave(r) + ave(c)
10	GSR	curve length	max(r) - max(c)
11	GSR	curve length	min(r) - min(c)
12	GSR	curve length	max(r) - min(c)
13	GSR	curve length	min(r) - max(c)
14	GSR	area	max(r) / max(c)
15	GSR	area	ave(r) - ave(c)
16	GSR	area	ave(r) + ave(c)
17	GSR	area	max(r) - max(c)
18	GSR	area	min(r) - min(c)
19	GSR	area	max(r) - min(c)
20	GSR	area	min(r) - max(c)
21	GSR	area	max(r) / max(c)
22	GSR	median of the derivative	ave(r) - ave(c)
23	GSR	median of the derivative	ave(r) + ave(c)
24	GSR	median of the derivative	max(r) - max(c)
25	GSR	median of the derivative	min(r) - min(c)
26	GSR	median of the derivative	max(r) - min(c)
27	GSR	median of the derivative	min(r) - max(c)
28	GSR	median of the derivative	max(r) / max(c)
29	GSR	min subtracted from the max	ave(r) - ave(c)
30	GSR	min subtracted from the max	ave(r) + ave(c)
31	GSR	min subtracted from the max	max(r) - max(c)
32	GSR	min subtracted from the max	min(r) - min(c)
33	GSR	min subtracted from the max	max(r) - min(c)
34	GSR	min subtracted from the max	min(r) - max(c)
35	GSR	min subtracted from the max	max(r) / max(c)
36	GSR	maximum of the signal	ave(r) - ave(c)
37	GSR	maximum of the signal	ave(r) + ave(c)
38	GSR	maximum of the signal	max(r) - max(c)
39	GSR	maximum of the signal	min(r) - min(c)
40	GSR	maximum of the signal	max(r) - min(c)
41	GSR	maximum of the signal	min(r) - max(c)
42	GSR	maximum of the signal	max(r) / max(c)
43	GSR	minimum of the signal	ave(r) - ave(c)
44	GSR	minimum of the signal	ave(r) + ave(c)
45	GSR	minimum of the signal	max(r) - max(c)
46	GSR	minimum of the signal	min(r) - min(c)
47	GSR	minimum of the signal	max(r) - min(c)
48	GSR	minimum of the signal	min(r) - max(c)
49	GSR	minimum of the signal	max(r) / max(c)
50	GSR	mean of derivative	ave(r) - ave(c)
51	GSR	mean of derivative	ave(r) + ave(c)
52	GSR	mean of derivative	max(r) - max(c)
53	GSR	mean of derivative	min(r) - min(c)
54	GSR	mean of derivative	max(r) - min(c)
55	GSR	mean of derivative	min(r) - max(c)
56	GSR	mean of derivative	max(r) / max(c)
57	HFEC	mean	ave(r) - ave(c)
58	HFEC	mean	ave(r) + ave(c)
59	HFEC	mean	max(r) - max(c)
60	HFEC	mean	min(r) - min(c)
61	HFEC	mean	max(r) - min(c)
62	HFEC	mean	min(r) - max(c)
63	HFEC	mean	max(r) / max(c)
64	HFEC	curve length	ave(r) - ave(c)
65	HFEC	curve length	ave(r) + ave(c)
66	HFEC	curve length	max(r) - max(c)
67	HFEC	curve length	min(r) - min(c)
68	HFEC	curve length	max(r) - min(c)
69	HFEC	curve length	min(r) - max(c)
70	HFEC	curve length	max(r) / max(c)
71	HFEC	area	ave(r) - ave(c)
72	HFEC	area	ave(r) + ave(c)
73	HFEC	area	max(r) - max(c)
74	HFEC	area	min(r) - min(c)
75	HFEC	area	max(r) - min(c)
76	HFEC	area	min(r) - max(c)
77	HFEC	area	max(r) / max(c)
78	HFEC	amplitude of the peaks	ave(r) - ave(c)
79	HFEC	amplitude of the peaks	ave(r) + ave(c)
80	HFEC	amplitude of the peaks	max(r) - max(c)
81	HFEC	amplitude of the peaks	min(r) - min(c)
82	HFEC	amplitude of the peaks	max(r) - min(c)
83	HFEC	amplitude of the peaks	min(r) - max(c)
84	HFEC	amplitude of the peaks	max(r) / max(c)
85	HFEC	dampcard	ave(r) - ave(c)
86	HFEC	dampcard	ave(r) + ave(c)
87	HFEC	dampcard	max(r) - max(c)
88	HFEC	dampcard	min(r) - min(c)
89	HFEC	dampcard	max(r) - min(c)
90	HFEC	dampcard	min(r) - max(c)
91	HFEC	dampcard	max(r) / max(c)
92	HFEC	number of peaks in cardio	ave(r) - ave(c)
93	HFEC	number of peaks in cardio	ave(r) + ave(c)
94	HFEC	number of peaks in cardio	max(r) - max(c)
95	HFEC	number of peaks in cardio	min(r) - min(c)
96	HFEC	number of peaks in cardio	max(r) - min(c)
97	HFEC	number of peaks in cardio	min(r) - max(c)
98	HFEC	number of peaks in cardio	max(r) / max(c)
99	HFEC	median of the derivative	ave(r) - ave(c)
100	HFEC	median of the derivative	ave(r) + ave(c)
101	HFEC	median of the derivative	max(r) - max(c)
102	HFEC	median of the derivative	min(r) - min(c)
103	HFEC	median of the derivative	max(r) - min(c)
104	HFEC	median of the derivative	min(r) - max(c)
105	HFEC	median of the derivative	max(r) / max(c)
106	HFEC	min subtracted from the max	ave(r) - ave(c)
107	HFEC	min subtracted from the max	ave(r) + ave(c)
108	HFEC	min subtracted from the max	max(r) - max(c)
109	HFEC	min subtracted from the max	min(r) - min(c)
110	HFEC	min subtracted from the max	max(r) - min(c)
111	HFEC	min subtracted from the max	min(r) - max(c)
112	HFEC	min subtracted from the max	max(r) / max(c)
113	HFEC	maximum	ave(r) - ave(c)
114	HFEC	maximum	ave(r) + ave(c)
115	HFEC	maximum	max(r) - max(c)
116	HFEC	maximum	min(r) - min(c)
117	HFEC	maximum	max(r) - min(c)
118	HFEC	maximum	min(r) - max(c)
119	HFEC	maximum	max(r) / max(c)
120	HFEC	minimum	ave(r) - ave(c)
121	HFEC	minimum	ave(r) + ave(c)
122	HFEC	minimum	max(r) - max(c)
123	HFEC	minimum	min(r) - min(c)
124	HFEC	minimum	max(r) - min(c)
125	HFEC	minimum	min(r) - max(c)
126	HFEC	minimum	max(r) / max(c)
127	HFEC	median of the derivative	ave(r) - ave(c)
128	HFEC	median of the derivative	ave(r) + ave(c)
129	HFEC	median of the derivative	max(r) - max(c)
130	HFEC	median of the derivative	min(r) - min(c)
131	HFEC	median of the derivative	max(r) - min(c)
132	HFEC	median of the derivative	min(r) - max(c)
133	HFEC	median of the derivative	max(r) / max(c)
134	HFEC	minampc	ave(r) - ave(c)
135	HFEC	minampc	ave(r) + ave(c)
136	HFEC	minampc	max(r) - max(c)
137	HFEC	minampc	min(r) - min(c)
138	HFEC	minampc	max(r) - min(c)
139	HFEC	minampc	min(r) - max(c)
140	HFEC	minampc	max(r) / max(c)

Fig.41: List of labels of all the features used in this project

141	LC	mean	ave(r) - ave(c)
142	LC	mean	ave(r) + ave(c)
143	LC	mean	max(r) - max(c)
144	LC	mean	min(r) - min(c)
145	LC	mean	max(r) - min(c)
146	LC	mean	min(r) - max(c)
147	LC	mean	max(r) / max(c)
148	LC	curve length	ave(r) - ave(c)
149	LC	curve length	ave(r) + ave(c)
150	LC	curve length	max(r) - max(c)
151	LC	curve length	min(r) - min(c)
152	LC	curve length	max(r) - min(c)
153	LC	curve length	min(r) - max(c)
154	LC	curve length	max(r) / max(c)
155	LC	area	ave(r) - ave(c)
156	LC	area	ave(r) + ave(c)
157	LC	area	max(r) - max(c)
158	LC	area	min(r) - min(c)
159	LC	area	max(r) - min(c)
160	LC	area	min(r) - max(c)
161	LC	area	max(r) / max(c)
162	LC	median of the derivative	ave(r) - ave(c)
163	LC	median of the derivative	ave(r) + ave(c)
164	LC	median of the derivative	max(r) - max(c)
165	LC	median of the derivative	min(r) - min(c)
166	LC	median of the derivative	max(r) - min(c)
167	LC	median of the derivative	min(r) - max(c)
168	LC	median of the derivative	max(r) / max(c)
169	LC	min subtracted from the max	ave(r) - ave(c)
170	LC	min subtracted from the max	ave(r) + ave(c)
171	LC	min subtracted from the max	max(r) - max(c)
172	LC	min subtracted from the max	min(r) - min(c)
173	LC	min subtracted from the max	max(r) - min(c)
174	LC	min subtracted from the max	min(r) - max(c)
175	LC	min subtracted from the max	max(r) / max(c)
176	LC	maximum	ave(r) - ave(c)
177	LC	maximum	ave(r) + ave(c)
178	LC	maximum	max(r) - max(c)
179	LC	maximum	min(r) - min(c)
180	LC	maximum	max(r) - min(c)
181	LC	maximum	min(r) - max(c)
182	LC	maximum	max(r) / max(c)
183	LC	minimum	ave(r) - ave(c)
184	LC	minimum	ave(r) + ave(c)
185	LC	minimum	max(r) - max(c)
186	LC	minimum	min(r) - min(c)
187	LC	minimum	max(r) - min(c)
188	LC	minimum	min(r) - max(c)
189	LC	minimum	max(r) / max(c)
190	LC	median of the derivative	ave(r) - ave(c)
191	LC	median of the derivative	ave(r) + ave(c)
192	LC	median of the derivative	max(r) - max(c)
193	LC	median of the derivative	min(r) - min(c)
194	LC	median of the derivative	max(r) - min(c)
195	LC	median of the derivative	min(r) - max(c)
196	LC	median of the derivative	max(r) / max(c)
197	DLC	mean	ave(r) - ave(c)
198	DLC	mean	ave(r) + ave(c)
199	DLC	mean	max(r) - max(c)
200	DLC	mean	min(r) - min(c)
201	DLC	mean	max(r) - min(c)
202	DLC	mean	min(r) - max(c)
203	DLC	mean	max(r) / max(c)
204	DLC	curve length	ave(r) - ave(c)
205	DLC	curve length	ave(r) + ave(c)
206	DLC	curve length	max(r) - max(c)
207	DLC	curve length	min(r) - min(c)
208	DLC	curve length	max(r) - min(c)
209	DLC	curve length	min(r) - max(c)
210	DLC	curve length	max(r) / max(c)

211	DLC	area	ave(r) - ave(c)
212	DLC	area	ave(r) + ave(c)
213	DLC	area	max(r) - max(c)
214	DLC	area	min(r) - min(c)
215	DLC	area	max(r) - min(c)
216	DLC	area	min(r) - max(c)
217	DLC	area	max(r) / max(c)
218	DLC	median of the derivative	ave(r) - ave(c)
219	DLC	median of the derivative	ave(r) + ave(c)
220	DLC	median of the derivative	max(r) - max(c)
221	DLC	median of the derivative	min(r) - min(c)
222	DLC	median of the derivative	max(r) - min(c)
223	DLC	median of the derivative	min(r) - max(c)
224	DLC	median of the derivative	max(r) / max(c)
225	DLC	min subtracted from the max	ave(r) - ave(c)
226	DLC	min subtracted from the max	ave(r) + ave(c)
227	DLC	min subtracted from the max	max(r) - max(c)
228	DLC	min subtracted from the max	min(r) - min(c)
229	DLC	min subtracted from the max	max(r) - min(c)
230	DLC	min subtracted from the max	min(r) - max(c)
231	DLC	min subtracted from the max	max(r) / max(c)
232	DLC	maximum	ave(r) - ave(c)
233	DLC	maximum	ave(r) + ave(c)
234	DLC	maximum	max(r) - max(c)
235	DLC	maximum	min(r) - min(c)
236	DLC	maximum	max(r) - min(c)
237	DLC	maximum	min(r) - max(c)
238	DLC	maximum	max(r) / max(c)
239	DLC	minimum	ave(r) - ave(c)
240	DLC	minimum	ave(r) + ave(c)
241	DLC	minimum	max(r) - max(c)
242	DLC	minimum	min(r) - min(c)
243	DLC	minimum	max(r) - min(c)
244	DLC	minimum	min(r) - max(c)
245	DLC	minimum	max(r) / max(c)
246	DLC	mean of derivative	ave(r) - ave(c)
247	DLC	mean of derivative	ave(r) + ave(c)
248	DLC	mean of derivative	max(r) - max(c)
249	DLC	mean of derivative	min(r) - min(c)
250	DLC	mean of derivative	max(r) - min(c)
251	DLC	mean of derivative	min(r) - max(c)
252	DLC	mean of derivative	max(r) / max(c)
253	LR	mean	ave(r) - ave(c)
254	LR	mean	ave(r) + ave(c)
255	LR	mean	max(r) - max(c)
256	LR	mean	min(r) - min(c)
257	LR	mean	max(r) - min(c)
258	LR	mean	min(r) - max(c)
259	LR	mean	max(r) / max(c)
260	LR	curve length	ave(r) - ave(c)
261	LR	curve length	ave(r) + ave(c)
262	LR	curve length	max(r) - max(c)
263	LR	curve length	min(r) - min(c)
264	LR	curve length	max(r) - min(c)
265	LR	curve length	min(r) - max(c)
266	LR	curve length	max(r) / max(c)
267	LR	area	ave(r) - ave(c)
268	LR	area	ave(r) + ave(c)
269	LR	area	max(r) - max(c)
270	LR	area	min(r) - min(c)
271	LR	area	max(r) - min(c)
272	LR	area	min(r) - max(c)
273	LR	area	max(r) / max(c)
274	LR	amplitude of the peaks	ave(r) - ave(c)
275	LR	amplitude of the peaks	ave(r) + ave(c)
276	LR	amplitude of the peaks	max(r) - max(c)
277	LR	amplitude of the peaks	min(r) - min(c)
278	LR	amplitude of the peaks	max(r) - min(c)
279	LR	amplitude of the peaks	min(r) - max(c)
280	LR	amplitude of the peaks	max(r) / max(c)

Fig.41: Continued

281	LR	number of the peaks	ave(r) - ave(c)
282	LR	number of the peaks	ave(r) + ave(c)
283	LR	number of the peaks	max(r) - max(c)
284	LR	number of the peaks	min(r) - min(c)
285	LR	number of the peaks	max(r) - min(c)
286	LR	number of the peaks	min(r) - max(c)
287	LR	number of the peaks	max(r) / max(c)
288	LR	inhal_divided_by_exhal	ave(r) - ave(c)
289	LR	inhal_divided_by_exhal	ave(r) + ave(c)
290	LR	inhal_divided_by_exhal	max(r) - max(c)
291	LR	inhal_divided_by_exhal	min(r) - min(c)
292	LR	inhal_divided_by_exhal	max(r) - min(c)
293	LR	inhal_divided_by_exhal	min(r) - max(c)
294	LR	inhal_divided_by_exhal	max(r) / max(c)
295	LR	dampr	ave(r) - ave(c)
296	LR	dampr	ave(r) + ave(c)
297	LR	dampr	max(r) - max(c)
298	LR	dampr	min(r) - min(c)
299	LR	dampr	max(r) - min(c)
300	LR	dampr	min(r) - max(c)
301	LR	dampr	max(r) / max(c)
302	LR	ieie	ave(r) - ave(c)
303	LR	ieie	ave(r) + ave(c)
304	LR	ieie	max(r) - max(c)
305	LR	ieie	min(r) - min(c)
306	LR	ieie	max(r) - min(c)
307	LR	ieie	min(r) - max(c)
308	LR	ieie	max(r) / max(c)
309	LR	median of the derivative	ave(r) - ave(c)
310	LR	median of the derivative	ave(r) + ave(c)
311	LR	median of the derivative	max(r) - max(c)
312	LR	median of the derivative	min(r) - min(c)
313	LR	median of the derivative	max(r) - min(c)
314	LR	median of the derivative	min(r) - max(c)
315	LR	median of the derivative	max(r) / max(c)
316	LR	min subtracted from the max	ave(r) - ave(c)
317	LR	min subtracted from the max	ave(r) + ave(c)
318	LR	min subtracted from the max	max(r) - max(c)
319	LR	min subtracted from the max	min(r) - min(c)
320	LR	min subtracted from the max	max(r) - min(c)
321	LR	min subtracted from the max	min(r) - max(c)
322	LR	min subtracted from the max	max(r) / max(c)
323	LR	maximum	ave(r) - ave(c)
324	LR	maximum	ave(r) + ave(c)
325	LR	maximum	max(r) - max(c)
326	LR	maximum	min(r) - min(c)
327	LR	maximum	max(r) - min(c)
328	LR	maximum	min(r) - max(c)
329	LR	maximum	max(r) / max(c)
330	LR	minimum	ave(r) - ave(c)
331	LR	minimum	ave(r) + ave(c)
332	LR	minimum	max(r) - max(c)
333	LR	minimum	min(r) - min(c)
334	LR	minimum	max(r) - min(c)
335	LR	minimum	min(r) - max(c)
336	LR	minimum	max(r) / max(c)
337	LR	mean of derivative	ave(r) - ave(c)
338	LR	mean of derivative	ave(r) + ave(c)
339	LR	mean of derivative	max(r) - max(c)
340	LR	mean of derivative	min(r) - min(c)
341	LR	mean of derivative	max(r) - min(c)
342	LR	mean of derivative	min(r) - max(c)
343	LR	mean of derivative	max(r) / max(c)
344	LR	minampr	ave(r) - ave(c)
345	LR	minampr	ave(r) + ave(c)
346	LR	minampr	max(r) - max(c)
347	LR	minampr	min(r) - min(c)
348	LR	minampr	max(r) - min(c)
349	LR	minampr	min(r) - max(c)
350	LR	minampr	max(r) / max(c)

351	UR	mean	ave(r) - ave(c)
352	UR	mean	ave(r) + ave(c)
353	UR	mean	max(r) - max(c)
354	UR	mean	min(r) - min(c)
355	UR	mean	max(r) - min(c)
356	UR	mean	min(r) - max(c)
357	UR	mean	max(r) / max(c)
358	UR	curve length	ave(r) - ave(c)
359	UR	curve length	ave(r) + ave(c)
360	UR	curve length	max(r) - max(c)
361	UR	curve length	min(r) - min(c)
362	UR	curve length	max(r) - min(c)
363	UR	curve length	min(r) - max(c)
364	UR	curve length	max(r) / max(c)
365	UR	area	ave(r) - ave(c)
366	UR	area	ave(r) + ave(c)
367	UR	area	max(r) - max(c)
368	UR	area	min(r) - min(c)
369	UR	area	max(r) - min(c)
370	UR	area	min(r) - max(c)
371	UR	area	max(r) / max(c)
372	UR	amplitude of the peaks	ave(r) - ave(c)
373	UR	amplitude of the peaks	ave(r) + ave(c)
374	UR	amplitude of the peaks	max(r) - max(c)
375	UR	amplitude of the peaks	min(r) - min(c)
376	UR	amplitude of the peaks	max(r) - min(c)
377	UR	amplitude of the peaks	min(r) - max(c)
378	UR	amplitude of the peaks	max(r) / max(c)
379	UR	dampr	ave(r) - ave(c)
380	UR	dampr	ave(r) + ave(c)
381	UR	dampr	max(r) - max(c)
382	UR	dampr	min(r) - min(c)
383	UR	dampr	max(r) - min(c)
384	UR	dampr	min(r) - max(c)
385	UR	dampr	max(r) / max(c)
386	UR	number of the peaks	ave(r) - ave(c)
387	UR	number of the peaks	ave(r) + ave(c)
388	UR	number of the peaks	max(r) - max(c)
389	UR	number of the peaks	min(r) - min(c)
390	UR	number of the peaks	max(r) - min(c)
391	UR	number of the peaks	min(r) - max(c)
392	UR	number of the peaks	max(r) / max(c)
393	UR	inhal_divided_by_exhal	ave(r) - ave(c)
394	UR	inhal_divided_by_exhal	ave(r) + ave(c)
395	UR	inhal_divided_by_exhal	max(r) - max(c)
396	UR	inhal_divided_by_exhal	min(r) - min(c)
397	UR	inhal_divided_by_exhal	max(r) - min(c)
398	UR	inhal_divided_by_exhal	min(r) - max(c)
399	UR	inhal_divided_by_exhal	max(r) / max(c)
400	UR	ieie	ave(r) - ave(c)
401	UR	ieie	ave(r) + ave(c)
402	UR	ieie	max(r) - max(c)
403	UR	ieie	min(r) - min(c)
404	UR	ieie	max(r) - min(c)
405	UR	ieie	min(r) - max(c)
406	UR	ieie	max(r) / max(c)
407	UR	median of the derivative	ave(r) - ave(c)
408	UR	median of the derivative	ave(r) + ave(c)
409	UR	median of the derivative	max(r) - max(c)
410	UR	median of the derivative	min(r) - min(c)
411	UR	median of the derivative	max(r) - min(c)
412	UR	median of the derivative	min(r) - max(c)
413	UR	median of the derivative	max(r) / max(c)
414	UR	min subtracted from the max	ave(r) - ave(c)
415	UR	min subtracted from the max	ave(r) + ave(c)
416	UR	min subtracted from the max	max(r) - max(c)
417	UR	min subtracted from the max	min(r) - min(c)
418	UR	min subtracted from the max	max(r) - min(c)
419	UR	min subtracted from the max	min(r) - max(c)
420	UR	min subtracted from the max	max(r) / max(c)

Fig.41: Continued

421	UR	maximum	ave(r) - ave(c)
422	UR	maximum	ave(r) + ave(c)
423	UR	maximum	max(r) - max(c)
424	UR	maximum	min(r) - min(c)
425	UR	maximum	max(r) - min(c)
426	UR	maximum	min(r) - max(c)
427	UR	maximum	max(r) / max(c)
428	UR	minimum	ave(r) - ave(c)
429	UR	minimum	ave(r) + ave(c)
430	UR	minimum	max(r) - max(c)
431	UR	minimum	min(r) - min(c)
432	UR	minimum	max(r) - min(c)
433	UR	minimum	min(r) - max(c)
434	UR	minimum	max(r) / max(c)
435	UR	mean of derivative	ave(r) - ave(c)
436	UR	mean of derivative	ave(r) + ave(c)
437	UR	mean of derivative	max(r) - max(c)
438	UR	mean of derivative	min(r) - min(c)
439	UR	mean of derivative	max(r) - min(c)
440	UR	mean of derivative	min(r) - max(c)
441	UR	mean of derivative	max(r) / max(c)
442	UR	minampr	ave(r) - ave(c)
443	UR	minampr	ave(r) + ave(c)
444	UR	minampr	max(r) - max(c)
445	UR	minampr	min(r) - min(c)
446	UR	minampr	max(r) - min(c)
447	UR	minampr	min(r) - max(c)
448	UR	minampr	max(r) / max(c)
449	GSR	standard deviation	ave(r) - ave(c)
450	GSR	standard deviation	ave(r) + ave(c)
451	GSR	standard deviation	max(r) - max(c)
452	GSR	standard deviation	min(r) - min(c)
453	GSR	standard deviation	max(r) - min(c)
454	GSR	standard deviation	min(r) - max(c)
455	GSR	standard deviation	max(r) / max(c)
456	HFEC	standard deviation	ave(r) - ave(c)
457	HFEC	standard deviation	ave(r) + ave(c)
458	HFEC	standard deviation	max(r) - max(c)
459	HFEC	standard deviation	min(r) - min(c)
460	HFEC	standard deviation	max(r) - min(c)
461	HFEC	standard deviation	min(r) - max(c)
462	HFEC	standard deviation	max(r) / max(c)
463	LC	standard deviation	ave(r) - ave(c)
464	LC	standard deviation	ave(r) + ave(c)
465	LC	standard deviation	max(r) - max(c)
466	LC	standard deviation	min(r) - min(c)
467	LC	standard deviation	max(r) - min(c)
468	LC	standard deviation	min(r) - max(c)
469	LC	standard deviation	max(r) / max(c)
470	DLC	standard deviation	ave(r) - ave(c)
471	DLC	standard deviation	ave(r) + ave(c)
472	DLC	standard deviation	max(r) - max(c)
473	DLC	standard deviation	min(r) - min(c)
474	DLC	standard deviation	max(r) - min(c)
475	DLC	standard deviation	min(r) - max(c)
476	DLC	standard deviation	max(r) / max(c)
477	LR	standard deviation	ave(r) - ave(c)
478	LR	standard deviation	ave(r) + ave(c)
479	LR	standard deviation	max(r) - max(c)
480	LR	standard deviation	min(r) - min(c)
481	LR	standard deviation	max(r) - min(c)
482	LR	standard deviation	min(r) - max(c)
483	LR	standard deviation	max(r) / max(c)
484	UR	standard deviation	ave(r) - ave(c)
485	UR	standard deviation	ave(r) + ave(c)
486	UR	standard deviation	max(r) - max(c)
487	UR	standard deviation	min(r) - min(c)
488	UR	standard deviation	max(r) - min(c)
489	UR	standard deviation	min(r) - max(c)
490	UR	standard deviation	max(r) / max(c)

491	HFEC	coeff_of_ARmod	ave(r) - ave(c)
492	HFEC	coeff_of_ARmod	ave(r) + ave(c)
493	HFEC	coeff_of_ARmod	max(r) - max(c)
494	HFEC	coeff_of_ARmod	min(r) - min(c)
495	HFEC	coeff_of_ARmod	max(r) - min(c)
496	HFEC	coeff_of_ARmod	min(r) - max(c)
497	HFEC	coeff_of_ARmod	max(r) / max(c)
498	HFEC	coeff_of_ARmod	ave(r) - ave(c)
499	HFEC	coeff_of_ARmod	ave(r) + ave(c)
500	HFEC	coeff_of_ARmod	max(r) - max(c)
501	HFEC	coeff_of_ARmod	min(r) - min(c)
502	HFEC	coeff_of_ARmod	max(r) - min(c)
503	HFEC	coeff_of_ARmod	min(r) - max(c)
504	HFEC	coeff_of_ARmod	max(r) / max(c)
505	HFEC	coeff_of_ARmod	ave(r) - ave(c)
506	HFEC	coeff_of_ARmod	ave(r) + ave(c)
507	HFEC	coeff_of_ARmod	max(r) - max(c)
508	HFEC	coeff_of_ARmod	min(r) - min(c)
509	HFEC	coeff_of_ARmod	max(r) - min(c)
510	HFEC	coeff_of_ARmod	min(r) - max(c)
511	HFEC	coeff_of_ARmod	max(r) / max(c)
512	HFEC	coeff_of_ARmod	ave(r) - ave(c)
513	HFEC	coeff_of_ARmod	ave(r) + ave(c)
514	HFEC	coeff_of_ARmod	max(r) - max(c)
515	HFEC	coeff_of_ARmod	min(r) - min(c)
516	HFEC	coeff_of_ARmod	max(r) - min(c)
517	HFEC	coeff_of_ARmod	min(r) - max(c)
518	HFEC	coeff_of_ARmod	max(r) / max(c)
519	HFEC	coeff_of_ARmod	ave(r) - ave(c)
520	HFEC	coeff_of_ARmod	ave(r) + ave(c)
521	HFEC	coeff_of_ARmod	max(r) - max(c)
522	HFEC	coeff_of_ARmod	min(r) - min(c)
523	HFEC	coeff_of_ARmod	max(r) - min(c)
524	HFEC	coeff_of_ARmod	min(r) - max(c)
525	HFEC	coeff_of_ARmod	max(r) / max(c)
526	HFEC	coeff_of_ARmod	ave(r) - ave(c)
527	HFEC	coeff_of_ARmod	ave(r) + ave(c)
528	HFEC	coeff_of_ARmod	max(r) - max(c)
529	HFEC	coeff_of_ARmod	min(r) - min(c)
530	HFEC	coeff_of_ARmod	max(r) - min(c)
531	HFEC	coeff_of_ARmod	min(r) - max(c)
532	HFEC	coeff_of_ARmod	max(r) / max(c)
533	HFEC	coeff_of_ARmod	ave(r) - ave(c)
534	HFEC	coeff_of_ARmod	ave(r) + ave(c)
535	HFEC	coeff_of_ARmod	max(r) - max(c)
536	HFEC	coeff_of_ARmod	min(r) - min(c)
537	HFEC	coeff_of_ARmod	max(r) - min(c)
538	HFEC	coeff_of_ARmod	min(r) - max(c)
539	HFEC	coeff_of_ARmod	max(r) / max(c)
540	HFEC	coeff_of_ARmod	ave(r) - ave(c)
541	HFEC	coeff_of_ARmod	ave(r) + ave(c)
542	HFEC	coeff_of_ARmod	max(r) - max(c)
543	HFEC	coeff_of_ARmod	min(r) - min(c)
544	HFEC	coeff_of_ARmod	max(r) - min(c)
545	HFEC	coeff_of_ARmod	min(r) - max(c)
546	HFEC	coeff_of_ARmod	max(r) / max(c)
547	HFEC	coeff_of_ARmod	ave(r) - ave(c)
548	HFEC	coeff_of_ARmod	ave(r) + ave(c)
549	HFEC	coeff_of_ARmod	max(r) - max(c)
550	HFEC	coeff_of_ARmod	min(r) - min(c)
551	HFEC	coeff_of_ARmod	max(r) - min(c)
552	HFEC	coeff_of_ARmod	min(r) - max(c)
553	HFEC	coeff_of_ARmod	max(r) / max(c)
554	HFEC	coeff_of_ARmod	ave(r) - ave(c)
555	HFEC	coeff_of_ARmod	ave(r) + ave(c)
556	HFEC	coeff_of_ARmod	max(r) - max(c)
557	HFEC	coeff_of_ARmod	min(r) - min(c)
558	HFEC	coeff_of_ARmod	max(r) - min(c)
559	HFEC	coeff_of_ARmod	min(r) - max(c)
560	HFEC	coeff_of_ARmod	max(r) / max(c)

Fig.41: Continued

561	HFEC	fund_fmax_cross_corr	ave(r) - ave(c)
562	HFEC	fund_fmax_cross_corr	ave(r) + ave(c)
563	HFEC	fund_fmax_cross_corr	max(r) - max(c)
564	HFEC	fund_fmax_cross_corr	min(r) - min(c)
565	HFEC	fund_fmax_cross_corr	max(r) - min(c)
567	HFEC	fund_fmax_cross_corr	min(r) - max(c)
568	LR	fund_fmax_cross_corr	max(r) / max(c)
569	LR	fund_fmax_cross_corr	ave(r) - ave(c)
570	LR	fund_fmax_cross_corr	ave(r) + ave(c)
571	LR	fund_fmax_cross_corr	max(r) - max(c)
572	LR	fund_fmax_cross_corr	min(r) - min(c)
573	LR	fund_fmax_cross_corr	max(r) - min(c)
574	LR	fund_fmax_cross_corr	min(r) - max(c)
575	HFUR	max_cross_correlation	max(r) / max(c)
576	HFUR	max_cross_correlation	ave(r) - ave(c)
577	HFUR	max_cross_correlation	ave(r) + ave(c)
578	HFUR	max_cross_correlation	max(r) - max(c)
579	HFUR	max_cross_correlation	min(r) - min(c)
580	HFUR	max_cross_correlation	max(r) - min(c)
581	HFUR	max_cross_correlation	min(r) - max(c)
582	HFUR	lag_max_cross_correlation	max(r) / max(c)
583	HFUR	lag_max_cross_correlation	ave(r) - ave(c)
584	HFUR	lag_max_cross_correlation	ave(r) + ave(c)
585	HFUR	lag_max_cross_correlation	max(r) - max(c)
586	HFUR	lag_max_cross_correlation	min(r) - min(c)
587	HFUR	lag_max_cross_correlation	max(r) - min(c)
588	HFUR	lag_max_cross_correlation	min(r) - max(c)
589	HFUR	min_cross_correlation	max(r) / max(c)
590	HFUR	min_cross_correlation	ave(r) - ave(c)
591	HFUR	min_cross_correlation	ave(r) + ave(c)
592	HFUR	min_cross_correlation	max(r) - max(c)
593	HFUR	min_cross_correlation	min(r) - min(c)
594	HFUR	min_cross_correlation	max(r) - min(c)
595	HFUR	min_cross_correlation	min(r) - max(c)
596	HFUR	lag_min_cross_correlation	max(r) / max(c)
597	HFUR	lag_min_cross_correlation	ave(r) - ave(c)
598	HFUR	lag_min_cross_correlation	ave(r) + ave(c)
599	HFUR	lag_min_cross_correlation	max(r) - max(c)
600	HFUR	lag_min_cross_correlation	min(r) - min(c)
601	HFUR	lag_min_cross_correlation	max(r) - min(c)
602	HFUR	lag_min_cross_correlation	min(r) - max(c)
603	HFEC	spec_HFEC_fund_freq	max(r) / max(c)
604	HFEC	spec_HFEC_fund_freq	ave(r) - ave(c)
605	HFEC	spec_HFEC_fund_freq	ave(r) + ave(c)
606	HFEC	spec_HFEC_fund_freq	max(r) - max(c)
607	HFEC	spec_HFEC_fund_freq	min(r) - min(c)
608	HFEC	spec_HFEC_fund_freq	max(r) - min(c)
609	HFEC	spec_HFEC_fund_freq	min(r) - max(c)
610	HFEC	spec_HFEC_2nd_harmonic	max(r) / max(c)
611	HFEC	spec_HFEC_2nd_harmonic	ave(r) - ave(c)
612	HFEC	spec_HFEC_2nd_harmonic	ave(r) + ave(c)
613	HFEC	spec_HFEC_2nd_harmonic	max(r) - max(c)
614	HFEC	spec_HFEC_2nd_harmonic	min(r) - min(c)
615	HFEC	spec_HFEC_2nd_harmonic	max(r) - min(c)
616	HFEC	spec_HFEC_2nd_harmonic	min(r) - max(c)
617	UR	spec_UR_fund_frequency	max(r) / max(c)
618	UR	spec_UR_fund_frequency	ave(r) - ave(c)
619	UR	spec_UR_fund_frequency	ave(r) + ave(c)
620	UR	spec_UR_fund_frequency	max(r) - max(c)
621	UR	spec_UR_fund_frequency	min(r) - min(c)
622	UR	spec_UR_fund_frequency	max(r) - min(c)
623	UR	spec_UR_fund_frequency	min(r) - max(c)
624	UR	spec_UR_2nd_harmonic	max(r) / max(c)
625	UR	spec_UR_2nd_harmonic	ave(r) - ave(c)
626	UR	spec_UR_2nd_harmonic	ave(r) + ave(c)
627	UR	spec_UR_2nd_harmonic	max(r) - max(c)
628	UR	spec_UR_2nd_harmonic6	min(r) - min(c)
629	UR	spec_UR_2nd_harmonic	max(r) - min(c)
630	UR	spec_UR_2nd_harmonic	min(r) - max(c)

631	HFUR	max_cross_spec_density	max(r) / max(c)
632	HFUR	max_cross_spec_density	ave(r) - ave(c)
633	HFUR	max_cross_spec_density	ave(r) + ave(c)
634	HFUR	max_cross_spec_density	max(r) - max(c)
635	HFUR	max_cross_spec_density	min(r) - min(c)
636	HFUR	max_cross_spec_density	max(r) - min(c)
637	HFUR	max_cross_spec_density	min(r) - max(c)
638	HFEC	coherency_HFEC & UR ff	max(r) / max(c)
639	HFEC	coherency_HFEC & UR ff	ave(r) - ave(c)
640	HFEC	coherency_HFEC & UR ff	ave(r) + ave(c)
641	HFEC	coherency_HFEC & UR ff	max(r) - max(c)
642	HFEC	coherency_HFEC & UR ff	min(r) - min(c)
643	HFEC	coherency_HFEC & UR ff	max(r) - min(c)
644	HFEC	coherency_HFEC & UR ff	min(r) - max(c)
645	HFEC	coherency_HFEC & UR sh	max(r) / max(c)
646	HFEC	coherency_HFEC & UR sh	ave(r) - ave(c)
647	HFEC	coherency_HFEC & UR sh	ave(r) + ave(c)
648	HFEC	coherency_HFEC & UR sh	max(r) - max(c)
649	HFEC	coherency_HFEC & UR sh	min(r) - min(c)
650	HFEC	coherency_HFEC & UR sh	max(r) - min(c)
651	HFEC	coherency_HFEC & UR sh	min(r) - max(c)
652	GSR	max_min_ISD_cont & relv	mean(r & c)
653	GSR	max_min_ISD_cont & relv	max(r & c)
654	GSR	max_min_ISD_cont & relv	min(r & c)
655	GSR	freq_max_ISD	mean(r & c)
656	GSR	freq_max_ISD	max(r & c)
657	GSR	freq_max_ISD	min(r & c)
658	GSR	area_under_ISD	mean(r & c)
659	GSR	area_under_ISD	max(r & c)
660	GSR	area_under_ISD	min(r & c)
661	HFEC	max_min_ISD	mean(r & c)
662	HFEC	max_min_ISD	max(r & c)
663	HFEC	max_min_ISD	min(r & c)
664	HFEC	freq_max_ISD	mean(r & c)
665	HFEC	freq_max_ISD	max(r & c)
666	HFEC	freq_max_ISD	min(r & c)
667	HFEC	area_under_ISD	mean(r & c)
668	HFEC	area_under_ISD	max(r & c)
669	HFEC	area_under_ISD	min(r & c)

Non-deceptive	Deceptive 1	Deceptive 2	Deceptive 3
QQ8R9OIO.011	QQ4Q1O83.011	QQ7LX5Q0.021	QQ8RAJ0C.011
QQ8R9OIO.021	QQ4Q1O83.021	QQ7LX5Q0.031	QQ8RAJ0C.021
QQ8R9OIO.031	QQ4Q1O83.031	QQ7MN2Y0.011	QQ8RAJ0C.031
QQ95LU1T.011	QQ4Q3MDC.011	QQ7MN2Y0.021	QQ9EUKVT.011
QQ95LU1T.021	QQ4Q3MDC.021	QQ7MN2Y0.031	QQ9EUKVT.021
QQ95LU1T.031	QQ4Q3MDC.031	QQ7TC5UF.011	QQ9EUKVT.031
QQAURNUS.021	QQ51DE36.011	QQ7TC5UF.021	QQ9IOOXO.021
QQAURNUS.031	QQ51DE36.021	QQ7TC5UF.031	QQ9IOOXO.041
QQAV53P6.011	QQ51DE36.041	QQ7TQVER.011	QQ9SOW8L.011
QQAV53P6.021	QQ6RQGH6.011	QQ7TQVER.021	QQ9SOW8L.021
QQAV53P6.031	QQ6RQGH6.021	QQ7TQVER.031	QQ9SOW8L.031
QQBQ4SHI.011	QQ6RQGH6.031	QQ7TVADC.011	QQ9SQIK9.011
QQBQ4SHI.021	QQ6RQGH6.041	QQ7TVADC.021	QQ9SQIK9.021
QQBQ4SHI.031	QQ6T711O.011	QQ7TVADC.031	QQ9SQIK9.031
QQBSS7WT.011	QQ6T711O.021	QQ7U2T4R.011	QQ9W0B9F.011
QQBSS7WT.021	QQ6T711O.031	QQ7U2T4R.021	QQ9W0B9F.031
QQBSS7WT.031	QQ6Z59IG.011	QQ7U2T4R.031	QQ9W0B9F.041
QQ7OXM60.021	QQ6Z59IG.021	QQ7YP7QU.011	QQ9U4FMU.011
QQ7RH0RO.011	QQ6Z59IG.031	QQ7YP7QU.021	QQ9U4FMU.021
QQ7RH0RO.021	QQ7PP9B9.011	QQ7YP7QU.031	QQ9U4FMU.031
QQ7RH0RO.031	QQ7PP9B9.021	QQ7YZOJ3.011	QQ9Y_SVF.011
QQ7R51P9.011	QQ7PP9B9.031	QQ7YZOJ3.021	QQ9Y_SVF.021
QQ7R51P9.021	QQ7PDU1X.011	QQ7YZOJ3.031	QQ9Y_SVF.031
QQ7R51P9.031	QQ7PDU1X.021	QQ8_0DPT.011	QQ9YH3QF.011
QQ9TDSP3.011	QQ7PDU1X.031	QQ8_0DPT.021	QQ9YH3QF.021
QQ9TDSP3.021	QQ7_PIPF.011	QQ8_0DPT.031	QQ9YH3QF.031
QQ9TDSP3.031	QQ7_PIPF.021	QQ8_0DPT.041	QQA2TT4C.011
QQA8OWOI.011	QQ7_PIPF.031	QQ8_2UQ9.011	QQA2TT4C.021
QQA8OWOI.021	QQ7_JT70.011	QQ8_2UQ9.021	QQA2TT4C.031
QQA8OWOI.031	QQ7_JT70.021	QQ8_2UQ9.031	QQA3HIRX.011
QQBT22O6.011	QQ7_JT70.031	QQ800IG6.011	QQA3HIRX.021
QQBT22O6.021	QQ738DYX.011	QQ800IG6.021	QQA3HIRX.031
QQBT22O6.031	QQ738DYX.021	QQ800IG6.031	QQA32UTF.011
QQBO9O_9.011	QQ738DYX.031	QQ82OIU9.011	QQA32UTF.021
QQBO9O_9.021	QQ75ULP9.011	QQ82OIU9.021	QQA32UTF.031
QQBO9O_9.031	QQ75ULP9.021	QQ82OIU9.031	QQA6U_IF.011
QQBC7PP6.011	QQ75ULP9.031	QQ82SUTX.011	QQA6U_IF.031
QQBC7PP6.021	QQ79_EYF.011	QQ82SUTX.021	QQA6U_IF.041
QQBC7PP6.031	QQ79_EYF.021	QQ82SUTX.031	QQAM4E3L.011
QQCHCK_O.011	QQ79_EYF.031	QQ860ZNU.011	QQAM4E3L.021
QQCHCK_O.021	QQ7BGDML.011	QQ860ZNU.021	QQAM4E3L.031
QQCHCK_O.031	QQ7BGDML.021	QQ860ZNU.031	QQARF2_X.011
QQCDTKP0.011	QQ7BGDML.031	QQ89U_ZR.011	QQARF2_X.021
QQCDTKP0.031	QQ7ETC8I.011	QQ89U_ZR.021	QQARF2_X.031
QQCDTKP0.041	QQ7ETC8I.021	QQ89U_ZR.031	QQAWA38X.011
QQCM5Y56.011	QQ7ETC8I.031	QQ8ATU26.011	QQAWA38X.021
QQCQQT8Y.011	QQ7JAQCS.011	QQ8ATU26.021	QQAWA38X.031
QQCQQT8Y.021	QQ7JAQCS.021	QQ8ATU26.031	QQAYXZGU.011
QQCQQT8Y.031	QQ7JAQCS.031	QQ8FGMVI.011	QQAYXZGU.021
QQCQQT8Y.041	QQ7LX5Q0.011	QQ8FGMVI.021	QQAYXZGU.031

Fig.42: List of polygraph files used in this experiment

6.3. USER INTERFACE

For an automated polygraph system as a real product, the existence of an user-friendly interface is unavoidable. MATLAB software environment provide an easy-to-use toolbox for creating various kinds of interactive interface classes. The following figure shows an interface used in one of my representations. This was made for a technically oriented user who is familiar with the algorithm. A simpler black-box version of a polygraph system, appropriate to the user's requests, can likewise be programmed.

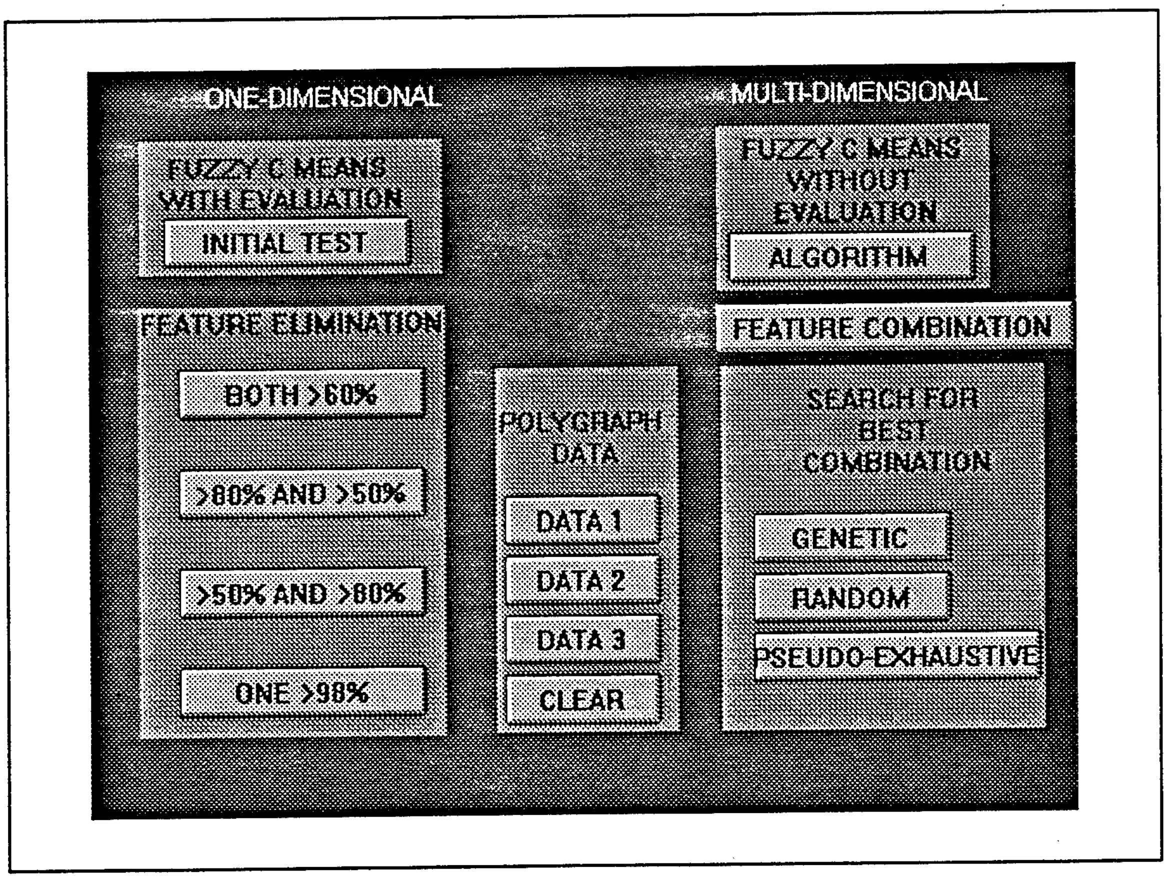

Fig.43: An example for a *technical user* interface

6.4. PROGRAM LISTINGS

(Implementation in MATLAB)

```
% THIS PROGRAM CALCULATESTHE CLUSTER CENTERS FOR
% A MULTIDIMENSIONAL FCM - C=2, CONST.

function V = c_center(X, U, m)

[colE, rowE] = size(X);
k=1:rowE;

%for the 1th class:

V1_numerator = U(1,k).^m  *  X(:,k)';
% (.*)==>(*): because the "numerator sum" is automatically
% included within the matrix multiplication.

V(1,:) = V1_numerator / sum( U(1,k).^m );
% V(1,:) [and V1_numerator] is a n-dimensional row-vector;
% n represents the number of the clustering features(n=30).

%for the 2nd class:

V2_numerator = U(2,k).^m  *  X(:,k)';
% (.*)==>(*): ...see above.

V(2,:) = V2_numerator / sum( U(2,k).^m );
% This is a n-dimensional row-vector and the cluster-center
% of the 2nd class.

V=V';                         % [nxc] matrix
return;
*********************************************************************
% FUZZY C-MEANS ALGORITHM FOR MULTI-DIMENSIONAL FCM.

%function best_Uik = fc_means(m, epsilon,X)
function [best_Uik, z] = fc_means(m, epsilon,X)
%function best_Uik = fc_means(m, epsilon)
%function [best_Uik, V, X] = fc_means(m, epsilon)
% think about the X

load init_u;                  % start with the initialization of the memb_fct
                              % (Uik ==> Vi)

% load init_v;                % or with the cluster centers
                              % (Vi ==> Uik)

%load set31;                  % including the data X respect. X1, X2, ...
%X=featmat;
%load set3me;X=Xselect;

%format long;                 % avoid errors by visual comparing the numbers
J_m = 100000000;              % to make sure the start is o.k.
z=0;
while J_m > epsilon

        V = c_center(X, U, m);

        U = memb_fct(X, V, m);

        Jtemp = J_m;
        J_m = j_mdim(X, V, U, m);

if epsilon <= 0.000005
        if (abs(J_m - Jtemp) <= .0000000001),
        %if J_m == Jtemp,            % to terminate the loop by reaching
                                     % the minimum of J_m.
          break,
        end
else
        if (abs(J_m - Jtemp) <= .0001),%---o.k.
        %if J_m == Jtemp,            % to terminate the loop by reaching
                                     % the minimum of J_m.
          break,
        end

end

%       t = abs(U - temp);           % tolerance value for the iteration

z=z+1;
 if rem(z,10) ==0
  fprintf('.\n');
 else
  fprintf('. ');
 end
end

 fprintf('\n');fprintf('________________\n');

best_Uik = U;
```

```
%Vnew = V;

% recall the extrem values: J_m =7.2308e+003

return;
```

****

```
% THIS PROGRAM CALCULATES THE OBJECTIVE FUNCTION
% FOR THE MULTIDIMENSIONAL FCM.

function J_m = j_mdim(X, V, U, m)

[colE,rowE] = size(X);
k = 1:rowE;

%for the 1th class:
V1asMatrix = V(:,1)*ones(1,rowE);                    % to avoid time-crunching for-loops

temp1 = ( X(:,k) - V1asMatrix )' * ( X(:,k) - V1asMatrix );   % trick: matrix-operation is faster;the sought norm is
                                                      % automatically the diagonal of temp1;

temp11 = (  (U(1,:).^m) .* (diag(temp1)')  );

J_out1 = sum(temp11);


%for the 2nd class:
V2asMatrix = V(:,2)*ones(1,rowE);                    % to avoid time-crunching for-loops

temp2 = ( X(:,k) - V2asMatrix )' * ( X(:,k) - V2asMatrix );   % see above

temp22 = (  (U(2,:).^m) .* (diag(temp2)')  );

J_out2 = sum(temp22);

J_m = J_out1 + J_out2;
return;
```

****

```
% THIS PROGRAM CALCULATES THE MEMBERSHIP VALUES FOR
% THE MULTIDIMENSIONAL FCM.

function U = memb_fct(X, V, m)

[colE,rowE] = size(X);
k = 1:rowE;

%for the 1th class:

V1asMatrix = V(:,1)*ones(1,rowE);
             % to avoid time-crunching for-loops

temp1 = ( X(:,k) - V1asMatrix )' * ( X(:,k) - V1asMatrix );
             % trick: matrix-operation is faster;the sought norm is
             % automatically the diagonal of temp1;

U_num(1,k) = ( diag(temp1)' ) .^ ( -1/(m-1) );

%for the 2nd class:

V2asMatrix = V(:,2)*ones(1,rowE);
             % to avoid time-crunching for-loops

temp2 = ( X(:,k) - V2asMatrix )' * ( X(:,k) - V2asMatrix );
             % see above

U_num(2,k) = ( diag(temp2)' ) .^ ( -1/(m-1) );


U(1,:) = U_num(1,k)  ./ (  U_num(1,k) + U_num(2,k)  );
U(2,:) = U_num(2,k)  ./ (  U_num(1,k) + U_num(2,k)  );

% If there is a third class, " U_num(3,k) ... "
% must be also considered.

return;
```

****

```
% FAST MULTIDIMENSIONAL EVALUATING PROGRAM
clear best_Uik;

%------without plots

best_Uik = fc_means(5, 0.0000005, Xselect);


figure(1);clg;hold on;
ss=1:100;
plot(ss,best_Uik(1,:),'+');plot(ss,best_Uik(2,:),'*b');
%plot(ss,best_Uik(3,:),'*b')
pause;
```

```
wrong_dcps = 0;
wrong_nons = 0;
figure(2);clg;hold on;
for s=1:100
        if best_Uik(2,s)>=.5
         plot(s,best_Uik(2,s),'*b');
                if s>50
                wrong_dcps=wrong_dcps+1;
                end
        else
         plot(s,best_Uik(2,s),'+');
                if s<=50
                wrong_nons=wrong_nons+1;
                end
        end
end

wpercent = wrong_dcps/50*100;
%fprintf('wrong_dcps, percent')
%[wrong_dcps, wpercent]
npercent = wrong_nons/50*100;
%fprintf('wrong_nons, npercent')
%[wrong_nons, npercent]

nn=(100-npercent);
ww=(100-wpercent);

fprintf('\n');fprintf('RIGHT DETECTIONS:');
fprintf('\n');fprintf('\n');fprintf('nD-clust D_clust');

[nn ww],
```

****

```
% USER INTERFACE
% Program B1. This program creates the start button.

figure(1);clg;
set(gcf,'color',[1 0 1])

button1 = uicontrol(gcf,...
'style','push',...
'position',[195 150 75 75],...
'string','START',...
'callback','bt_choic');
```

****

```
% USER INTERFACE
%Program B2. This program displays choices to run the various programs.


clf reset
set(gcf,'color',[0 0 1])

title('ONE-DIMENSIONAL                    MULTI-DIMENSIONAL')

axis off

frm2 = uicontrol(gcf,...
'style','text',...
'position',[25 40 155 200]);

tt2 = uicontrol(gcf,...
'style','text',...
'string','FEATURE ELIMINATION',...
'position',[25 215 155 40]);

frm4 = uicontrol(gcf,...
'style','frame',...
'position',[25 270 155 70]);

tt4 = uicontrol(gcf,...
'style','text',...
'string','FUZZY C MEANS WITH EVALUATION',...
'position',[35 288 125 45]);


button3 = uicontrol(gcf,...
'style','push',...
'position',[38 275 125 25],...
'string','INITIAL TEST',...
'callback','mega_tst');

frm = uicontrol(gcf,...
'style','frame',...
'position',[205 40 95 185]);

tt = uicontrol(gcf,...
'style','text',...
```

```
'string','POLYGRAPH DATA',...
'position',[207 165 85 40]);

button13 = uicontrol(gcf,...
'style','push',...
'position',[210 75 80 25],...
'string','DATA 3',...
'callback','load ftx3');

button14 = uicontrol(gcf,...
'style','push',...
'position',[210 105 80 25],...
'string','DATA 2',...
'callback','load ftx2');

button15 = uicontrol(gcf,...
'style','push',...
'position',[210 135 80 25],...
'string','DATA 1',...
'callback','load ftx1');

button16 = uicontrol(gcf,...
'style','push',...
'position',[210 45 80 25],...
'string','CLEAR',...
'callback','clear');

button17 = uicontrol(gcf,...
'style','push',...
'position',[45 200 125 25],...
'string','BOTH >60%',...
'callback','mega_i');

button18 = uicontrol(gcf,...
'style','push',...
'position',[45 150 125 25],...
'string','>80% AND >50%',...
'callback','mega_ii');

button19 = uicontrol(gcf,...
'style','push',...
'position',[45 100 125 25],...
'string','>50% AND >80%',...
'callback','mega_iii');

button20 = uicontrol(gcf,...
'style','push',...
'position',[45 50 125 25],...
'string','ONE >98%',...
'callback','mega_iv');

frm3 = uicontrol(gcf,...
'style','frame',...
'position',[320 40 165 185]);

tt3 = uicontrol(gcf,...
'style','text',...
'string','SEARCH FOR BEST COMBINATION',...
'position',[350 150 120 65]);

button21 = uicontrol(gcf,...
'style','push',...
'position',[318 230 192 25],...
'string','FEATURE COMBINATION',...
'callback','initfast');

frm5 = uicontrol(gcf,...
'style','frame',...
'position',[318 260 140 85]);

tt5 = uicontrol(gcf,...
'style','text',...
'string','FUZZY C MEANS WITHOUT EVALUATION',...
'position',[332 275 115 65]);

button4 = uicontrol(gcf,...
'style','push',...
'position',[325 265 125 25],...
'string','ALGORITHM',...
'callback','fc_means');

button22 = uicontrol(gcf,...
'style','push',...
'position',[337 125 100 25],...
'string','GENETIC',...
'callback','genetic4');

button23 = uicontrol(gcf,...
'style','push',...
'position',[337 95 100 25],...
```

```
'string','RANDOM',...
'callback','random');

button24 = uicontrol(gcf,...
'style','push',...
'position',[337 65 145 25],...
'string','PSEUDO-EXHAUSTIVE',...
'callback','feature4');
```

```
************************************************************************
% THIS PROGRAM COMPARES RESULTS BY DIFFERENT SET-UPS
% OF THE 'm'. AN EXAMPLE:

w_comp=zeros(1,669);
n_comp=zeros(1,669);

index=[1 3 5 15 17 19 22 29 30 31 33 36 37 38 39 40 50];
selindex=1:17;

w_comp(index) = selw_percent(selindex) - w_percent(index);
n_comp(index) = seln_percent(selindex) - n_percent(index);

Rindex=[70 141 155 177 197 200 202 211 214 216 235 449 450 453 458 462 600];
selindex=18:34;

w_comp(Rindex) = selw_percent(selindex) - w_percent(Rindex);
n_comp(Rindex) = seln_percent(selindex) - n_percent(Rindex);


%for 11 newis;

newindices=[4 12 18 52 68 82 176 395 451 459 460 ];
w_comp(newindices) = w_percent(newindices);
n_comp(newindices) = n_percent(newindices);

in=[1 3 4 5 12 15 17 18 19 22 29 30 31 33 36 37 38 39 40 50 52 68 70 82 141 155 ...
176 177 197 200 202 211 214 216 235 395 449 450 451 453 458 459 460 462 600];

[in;m2w_percent;m2n_percent;w;w_comp(in) ;n_comp(in)]'
```

```
************************************************************************
% ANOTHER EXAMPLE:

w_comp=zeros(1,669);
n_comp=zeros(1,669);

index=[1 3 4 5 12 15 17 18 19 22 29 30 31 33 36 37 38 39 40 50 52 68 ...
70 82 141 155 176 177 197 200 211 214 216 235 395 449 450 451];
selindex=1:38;

w_comp(index) = selw_percent(selindex) - w_percent(index);
n_comp(index) = seln_percent(selindex) - n_percent(index);

Rindex=[453 458 459 460 462 600];
selindex=40:45;

w_comp(Rindex) = selw_percent(selindex) - w_percent(Rindex);
n_comp(Rindex) = seln_percent(selindex) - n_percent(Rindex);


%for 1 newy;

newindices=[452];
w_comp(newindices) = w_percent(newindices);
n_comp(newindices) = n_percent(newindices);

in=[1 3 4 5 12 15 17 18 19 22 29 30 31 33 36 37 38 39 40 50 52 68 ...
70 82 141 155 176 177 197 200 211 214 216 235 395 449 450 451 452 ...
453 458 459 460 462 600];

[in;m2w_percent;m2n_percent;w;w_comp(in) ;n_comp(in)]'
```

```
************************************************************************
% THIS PROGRAM SELECT AND EVALUATE FEATURE GROUPS
% ACCORDING TO THE THRESHOLD.

dimension=669;

l=0;
for g=1:dimension
%---------------------ATTENTION: Change parameters for m=3...

 if( (n_percent(g)<=40) & (w_percent(g)<=40) )

 l=l+1;
 gg(l)=g;
 m2wrong_dcps(l)=wrong_dcps(g);
 m2w_percent(l)=w_percent(g);

 m2w_ok(l)=100-m2w_percent(l);
```

```
  m2wrong_nons(l)=wrong_nons(g);
  m2n_percent(l)=n_percent(g);

 m2n_ok(l)=100-m2n_percent(l);

  m2z(l)=z(g);

  if( (n_percent(g)<=25) | (w_percent(g)<=25) )
  w(l)=1.1111;
  else
  w(l)=0;
  end

 end

end
l

fprintf('m2ft_#, m2wrong_dcps, m2w_ok, m2wrong_nons, m2n_ok, m2iterations, bests');
h=1:l;
[gg(h)
m2wrong_dcps(h)
m2w_ok(h)
m2wrong_nons(h)
m2n_ok(h)
m2z(h)
w(h)]'

*******************************************************************

% THIS PROGRAM REPRESENTS ONE THE RANDOM SEARCH
% FOR 4-TUPLE FEATURE COMBINATIONS.

indi=0;
for i=1:10000

aaa = round(10*rand(1,4)); %----------4*ft--&--size of no=14
%            if aaa(1)>=7, aaa(1)=aaa(1)-5;end;
%            if aaa(2)>=7, aaa(2)=aaa(2)-5;end;
%            if aaa(3)>=7, aaa(3)=aaa(3)-5;end;

if aaa(1)==0, aaa(1)=11;end;
if aaa(2)==0, aaa(2)=12;end;
if aaa(3)==0, aaa(3)=13;end;
if aaa(4)==0, aaa(4)=14;end;

while ( (aaa(1)==aaa(2)) | (aaa(1)==aaa(3)) | (aaa(2)==aaa(3)) ...
| (aaa(2)==aaa(4)) | (aaa(1)==aaa(4)) ...
| (aaa(3)==aaa(4)) )
            aaa = round(10*rand(1,4));
%            if aaa(1)>=7, aaa(1)=aaa(1)-5;end;
%            if aaa(2)>=7, aaa(2)=aaa(2)-5;end;
%            if aaa(3)>=7, aaa(3)=aaa(3)-5;end;
            if aaa(1)==0, aaa(1)=11;end;
            if aaa(2)==0, aaa(2)=12;end;
            if aaa(3)==0, aaa(3)=13;end;
            if aaa(4)==0, aaa(4)=14;end;
end,

i,
indi,
aaa,

clear Xselect;
Xselect=Xsel(aaa,:);

initfast;

%--------------ATTENTION: LIMITATIONS ---------* %if *---------

%if(  ((nn>=80) & (ww>=80))   |   ((nn>=84) | (ww>=84))   )
if (((nn>=81)&(ww>=81)) | ((nn>=86)&(ww>=79)))        %--------- && 4*ft x3m5m2
%if ( (nn>=70) & (ww>=80) )                            %---------4*ft x1m5
            indi=indi+1;
            a1_combin(indi) = aaa(1);
            a2_combin(indi) = aaa(2);
            a3_combin(indi) = aaa(3);
            a4_combin(indi) = aaa(4);%----------4*ft
            n_combres(indi) = nn;
            w_combres(indi) = ww;
            fprintf('>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>');
            size(a1_combin)
            fprintf('>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>');
end

end

j=1:indi;
[a1_combin(j)
a2_combin(j)
```

```
a3_combin(j)
a4_combin(j)
n_combres(j)
w_combres(j)]'

**************************************************************************

% This program exhaustively tests all possible combinations of
% size eight in x3 from the number of features. It then records the ones
% that meet the if-then criteria below.
% clear('init') for normal initialization.

load x3

features=[81 111 450 452 197 459 30 ]
n=length(features)

for f=1:n
 Xsel(f,1:100)=x3(features(f),1:100);
end

if exist('init')==1
		% program continuation. No need to initialize other variables.
		i1=init(1);
		i2=init(2);
		i3=init(3);
		i4=init(4);
		i5=init(5);
		i6=init(6);
		i7=init(7);
		i8=init(8);
else
		% initialize all variables.
		indi=0;
		record=[];
		i1=1;
		i2=2;
		i3=3;
		i4=4;
		i5=5;
		i6=6;
		i7=7;
		i8=8;
end


while i1<=n-7
while i2<=n-6
while i3<=n-5
while i4<=n-4
while i5<=n-3
while i6<=n-2
while i7<=n-1
while i8<=n

aaa=[i1 i2 i3 i4 i5 i6 i7 i8]
indi

clear Xselect;
Xselect=Xsel(aaa,:);

initfast;

%--------------ATTENTION: LIMITATIONS ----------" %if "-----------
ave = (nn+ww)/2;

if( ((nn>=81)&(ww>=81)) | (ave>=83) )
		indi=indi+1;
		record=[record ; features(aaa) nn ww];
		fprintf('>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>');
		[features(aaa) nn ww]
end

i8=i8+1;
end		% end i8 loop
i7=i7+1;
i8=i7+1;
end		% end i7 loop
i6=i6+1;
i7=i6+1;
i8=i7+1;
end		% end i6 loop
i5=i5+1;
i6=i5+1;
i7=i6+1;
i8=i7+1;
end		% end i5 loop
i4=i4+1;
i5=i4+1;
i6=i5+1;
i7=i6+1;
```

```
i8=i7+1;
end            % end i4 loop
i3=i3+1;
i4=i3+1;
i5=i4+1;
i6=i5+1;
i7=i6+1;
i8=i7+1;
end            % end i3 loop
i2=i2+1;
i3=i2+1;
i4=i3+1;
i5=i4+1;
i6=i5+1;
i7=i6+1;
i8=i7+1;
end            % end i2 loop
i1=i1+1;
i2=i1+1;
i3=i2+1;
i4=i3+1;
i5=i4+1;
i6=i5+1;
i7=i6+1;
i8=i7+1;
end            % end i1 loop

record

************************************************************************

% Genetic algorithm in search of the optimal n-tuple
% from a gene pool of features.
% This version records the actual feature numbers in the
% matrix 'record', not the index!!
% x3. Set m in initfast.
% set init=1 for automatic initialization

comment='x3, m=5, 15-tuple.'
n=15;
load x3
clear Xselect;
features=[9 11 30 50 39 81 235 358 359 363 449 197 29 450 453 457 458 478 ...
          111 452 482 361 15 36 37 32 8 67 79 460]

% features=[4 5 8 9 12 18 19 22 29 30 33 36 39 40 50 56 62 76 79 81 ...
%           111 114 163 197 235 358 359 361 363 403 449 450 452 453 456 457 ...
%           458 477 478 482 534 625 ]

feature_num=length(features)

for f=1:feature_num
 Xsel(f,1:100)=x3(features(f),1:100);
end
clear x3;
clear average_fitness;

if init==1
          % initialize population size, crossover rate, mutation rate, etc.
          population_size=200;
          mutation_rate=0.001;
          crossover_rate=0.7;
          record=zeros(20,n+3);
          indi=0;

          % initialize population
          rand('uniform');
          population=fix((feature_num - .0000001) .* rand(population_size,n)) + 1;
end

% start evolution
for generation=1:100000
generation

% test the population for fitness
for f = 1:population_size
Xselect = Xsel(population(f,:),:);%
initfast;                              % test each individual

fitness(f) = abs((nn+ww)/2 - 20);      % subtract 20 to exaggerate the
                                                % difference in fitness ratio
          %if ( ((nn>=70)&(ww>=70)) | (fitness>=56) | ((nn<=20)&(ww<=20)) )
          if (  (fitness(f)>=65)  |  ((nn<=20)&(ww<=20))  )
                    indi=indi+1
                    record(indi,:) = [features(population(f,:)) generation nn ww];%
                    [features(population(f,:)) generation nn ww]
          end
end

% display average fitness in percentage
average_fitness(generation)=mean(fitness) + 20
```

```
% REPRODUCTION !!
% reorder the fitness values for easier computation
fit_measure(1)=fitness(1);
for f=2:population_size
fit_measure(f)=fit_measure(f-1)+fitness(f);
end

for f=1:population_size
% randomly pick one individual to copy into the new population
% individuals with higher fitness values are more likely to survive
temp=fit_measure(population_size) .* rand;
index=find(abs(fit_measure-temp) == min(abs(fit_measure-temp)));
        if temp <= fit_measure(index(1))
                new_population(f,:)=population(index(1),:);%
        else
                new_population(f,:)=population(index(1)+1,:);%
        end
end
population=new_population;

% CROSSOVER !!
f=1;
while f <= population_size
        if rand <= crossover_rate
                mate = f;
                crossover = 0;
                while (f < population_size) & (crossover==0)
                        f=f+1;
                        if rand <= crossover_rate
                          % actual crossover
                          crossover = 1;
                          temp=fix((n - 1.00001) .* rand) + 2;%
                          gene_temp=population(mate,temp:n);%
                          population(mate,temp:n)=population(f,temp:n);%
                          population(f,temp:n)=gene_temp;
                        end
                end
        end
        f=f+1;
end

% MUTATION !!
% Note: Modified Aug. 19 due to a bug
num_mutation=population_size .* mutation_rate .* n .* (randn + 1);
for f=1:num_mutation
 population(fix((population_size-0.000001).*rand+1),fix((n-0.00001)*rand+1))...
        = fix((feature_num - 0.000001) * rand + 1);
end

% save record in case of crashing
save crashrec comment record average_fitness

% go to next generation
end

% display record of good individuals in history
comment
record

% [sort(record(1:indi,1:n)')' record(1:indi,n+1:n+3)]

************************************************************************
% SELECTION AND INITIALIZATION OF THE DATA CENTERS
% FOR THE LMS FILTER.

% "initrain_sess" = Polygraph sessions which are used for
% INITialization of the "data_centers" and TRAINing.

% The "initrain" sessions are set in a way that the 1st part
% (before the "border") represents the non-decptive and the
% 2nd part (after the border) the deceptive sessions.

clear;
%*** To be set for each polydat_i (ftx3, ftx2, ftx1): ******************
%*                                                                     *
        whichfeatures_3 = [1:30];
        nondsessions_3 = [11:50];
                %[1 6 8 9 12 16 18 21 24 27 28 32 35 44 48];
        dcpsessions_3 = [51:90];
                %[51 53 58 59 63 67 72 75 82 85 88 89 93 95 100];
%*                                                                     *
        whichfeatures_2 = [];
        nondsessions_2 = [];
        dcpsessions_2 = [];
%*                                                                     *
        whichfeatures_1 = [];
        nondsessions_1 = [];
        dcpsessions_1 = [];
%*                                                                     *
```

```
%* ATTENTION: The DIMENSION of each "whichfeatures_..." is to be equal!      *
%* (or zero)                                                                 *
%*****************************************************************************

if length(whichfeatures_3) ~= length(whichfeatures_2) | ...
  length(whichfeatures_2) ~= length(whichfeatures_1) ,

        fprintf('!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!\n');
        fprintf('Check "whichfeatures"! They are different big!\n');
        fprintf('The dimensions are as following:\n');
        fprintf('\n');
        fprintf('   1st  2nd  3rd\n');
        disp( [length(whichfeatures_1), length(whichfeatures_2), ...
        length(whichfeatures_3)] )
        fprintf('\n');
        fprintf('YOU DO NOT NEED TO CHANGE THE EMPTY ONES!\n');
        fprintf('IF THAT'S THE CASE: PRESS ANY KEY TO CONTINUE.\n');
        fprintf('!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!\n');
        pause;

end;


border = length(nondsessions_3) + length(nondsessions_2) ...
   + length(nondsessions_1);


%%%% polydat_3:

if size(nondsessions_3,1) ~= 0,

        load c:\users\ramin\fcm\multidim\ftx3;

        dim = length(whichfeatures_3);
        f=1:dim;
        Ntemp_3(f,:) = x3(whichfeatures_3(f), nondsessions_3);
        Dtemp_3(f,:) = x3(whichfeatures_3(f), dcpsessions_3);

        clear x3;
end;

%%%% polydat_2

if size(nondsessions_2,1) ~= 0,

        load c:\users\ramin\fcm\multidim\ftx2;

        dim = length(whichfeatures_2);
        f=1:dim;
        Ntemp_2(f,:) = x2(whichfeatures_2(f), nondsessions_2);
        Dtemp_2(f,:) = x2(whichfeatures_2(f), dcpsessions_2);

        clear x2;
end;

%%%% polydat_1

if size(nondsessions_1,1) ~= 0,

        load c:\users\ramin\fcm\multidim\ftx1;

        dim = length(whichfeatures_1);
        f=1:dim;
        Ntemp_1(f,:) = x1(whichfeatures_1(f), nondsessions_1);
        Dtemp_1(f,:) = x1(whichfeatures_1(f), dcpsessions_1);

        clear x1;
end;

initrain_sess = [Ntemp_3'; Ntemp_2'; Ntemp_1'; ...
                        Dtemp_3'; Dtemp_2'; Dtemp_1'];

howmany = size(initrain_sess,1);


mesh(initrain_sess);


% TWO FEATURES AT A TIME - PLOT EXAMPLE:
%plot(initrain_sess(1:40,1),initrain_sess(1:40,4),'.y')
%hold on
%plot(initrain_sess(41:80,1),initrain_'sess(41:80,4),'.r')

*****************************************************************************

% SELECTION AND INITIALIZATION FOR LMS FILTER.

% The "initrain" data represents Polygraph sessions which are used for
% INITialization and TRAINing of the "data_centers" and input data.
```

```
% The "initrain" data are set in a way that the 1st part - before the
% "(TC_)border" - represents the non-decptive and the second part
% - after the "(TC_)border" -  the deceptive sessions.

% The prefix "nond" represents the non_decptive, and "dcp" the deceptive
% elements.

clear;
%*********************************************************************

%********* TO BE SET FOR EACH polydat_i (ftx3, ftx2, ftx1): *******
%*                                                                *
%* First for the data_centers:                                    *
%*                                                                *
            nondsessions_3 = [1:20];
                        %[1 6 8 9 12 16 18 21 24 27 28 32 35 44 48];
            dcpsessions_3 = [51:70];
                        %[51 53 58 59 63 67 72 75 82 85 88 89 93 95 100];
%*                                                                *
            nondsessions_2 = [];
            dcpsessions_2 = [];
%*                                                                *
            nondsessions_1 = [];
            dcpsessions_1 = [];
%*                                                                *
%*                                                                *
%* Now for the input data for which the filter is to be (T)rained *
%* to (C)lassify:                                                 *
%*                                                                *
            TC_nondsessions_3 = [1:30];
            TC_dcpsessions_3 = [51:80];                           *
                                                                  *
            TC_nondsessions_2 = [];
            TC_dcpsessions_2 = [];
%*                                                                *
            TC_nondsessions_1 = [];
            TC_dcpsessions_1 = [];
%*                                                                *
%*                                                                *
%* And finally for the selected features:                         *
%*                                                                *
            whichfeatures_3 = [1:30];
            whichfeatures_2 = [];
            whichfeatures_1 = [];
%*                                                                *
%* ATTENTION: The DIMENSION of each "whichfeatures_..." is to be equal! *
%* (or zero)                                                      *
%*****************************************************************

if length(whichfeatures_3) ~= length(whichfeatures_2) | ...
  length(whichfeatures_2) ~= length(whichfeatures_1) ,

            fprintf('!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!\n');
            fprintf('Check "whichfeatures"!  They are different big!\n');
            fprintf('The dimensions are as following:\n');
            fprintf('\n');
            fprintf('   1st   2nd   3rd\n');
            disp( [length(whichfeatures_1), length(whichfeatures_2), ...
            length(whichfeatures_3)] )
            fprintf('\n');
            fprintf('YOU DO NOT NEED TO CHANGE THE EMPTY ONES!\n');
            fprintf('IF THAT'S THE CASE: PRESS ANY KEY TO CONTINUE.\n');
            fprintf('!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!\n');
            pause;

end;

border = length(nondsessions_3) + length(nondsessions_2) ...
    + length(nondsessions_1);

TC_border = length(TC_nondsessions_3) + length(TC_nondsessions_2) ...
                + length(TC_nondsessions_1);


%%% polydat_3:

dim = length(whichfeatures_3);
if dim ~= 0,

            load c:\users\ramin\fcm\multidim\ftx3;
            f=1:dim;

            if length(TC_nondsessions_3) ~= 0,
            TC_Ntemp_3(f,:) = x3(whichfeatures_3(f), TC_nondsessions_3);
            end;

            if length(TC_dcpsessions_3) ~= 0,
            TC_Dtemp_3(f,:) = x3(whichfeatures_3(f), TC_dcpsessions_3);
            end;
```

```
		if length(nondsessions_3) ~= 0,
		Ntemp_3(f,:) = x3(whichfeatures_3(f), nondsessions_3);
		end;

		if length(dcpsessions_3) ~= 0,
		Dtemp_3(f,:) = x3(whichfeatures_3(f), dcpsessions_3);
		end;

		clear x3;
end;


%%% polydat_2

dim = length(whichfeatures_2);
if dim ~= 0,

		load c:\users\ramin\fcm\multidim\ftx2;
		f=1:dim;

		if length(TC_nondsessions_2) ~= 0,
		TC_Ntemp_2(f,:) = x2(whichfeatures_2(f), TC_nondsessions_2);
		end;

		if length(TC_dcpsessions_2) ~= 0,
		TC_Dtemp_2(f,:) = x2(whichfeatures_2(f), TC_dcpsessions_2);
		end;

		if length(nondsessions_2) ~= 0,
		Ntemp_2(f,:) = x2(whichfeatures_2(f), nondsessions_2);
		end;

		if length(dcpsessions_2) ~= 0,
		Dtemp_2(f,:) = x2(whichfeatures_2(f), dcpsessions_2);
		end;

		clear x2;
end;


%%% polydat_1

dim = length(whichfeatures_1);
if dim ~= 0,

		load c:\users\ramin\fcm\multidim\ftx1;
		f=1:dim;

		if length(TC_nondsessions_1) ~= 0,
		TC_Ntemp_1(f,:) = x1(whichfeatures_1(f), TC_nondsessions_1);
		end;

		if length(TC_dcpsessions_1) ~= 0,
		TC_Dtemp_1(f,:) = x1(whichfeatures_1(f), TC_dcpsessions_1);
		end;

		if length(nondsessions_1) ~= 0,
		Ntemp_1(f,:) = x1(whichfeatures_1(f), nondsessions_1);
		end;

		if length(dcpsessions_1) ~= 0,
		Dtemp_1(f,:) = x1(whichfeatures_1(f), dcpsessions_1);
		end;

		clear x1;
end;

TC_initrain = [TC_Ntemp_3'; TC_Ntemp_2'; TC_Ntemp_1'; ...
			TC_Dtemp_3'; TC_Dtemp_2'; TC_Dtemp_1'];

cent_initrain = [Ntemp_3'; Ntemp_2'; Ntemp_1'; ...
				Dtemp_3'; Dtemp_2'; Dtemp_1'];

**********************************************************************
% LMS FUZZY ADAPTIVE FILTER.

function [new_theta, new_data_centers, new_sigma, output_label] = ...
adaptzzy(theta, data_centers, sigma, input_vect, desire, step)
%fprintf('size(theta):');size(theta),
%fprintf('size(sigma):');size(sigma),

% Get the dimensions of matrices and verify their consistency:
[label_no, ft_no] = size(data_centers);
if ([label_no, ft_no] ~= size(sigma)) | ([1, ft_no] ~=size(input_vect)) |...
  ([label_no, 1] ~= size(theta))

		error('matrix dimensions are wrong! ')
end;
%+++
```

```
% Evaluate Gaussian membershipfunctions:

distances = (ones(label_no,1) * input_vect) - data_centers;
%fprintf('size(distances):');size(distances),
% To creat compatible dimensions: Fill input_vect down into an
% (label_no x ft_no) matrix, so that it is the same input for all
% (label_no) rules, and then subtract data_centers from it.

a = exp(  -0.5 .* sum( ((distances ./ sigma) .^2 )' )'  );
% Without "sum":  a = Uik i.e. membership values
% etc.etc...(conventional way)
%+++
%fprintf('size(a):');size(a),

% Centroidal defuzzification:
b = sum(a);%fprintf('size(b):');size(b),
output_label = sum(theta .* a) / b;
%+++


% Adaption:

temp1 = step .* (desire - output_label) .* a ./b;
new_theta = theta + temp1;

temp2 = ( (temp1 .* (theta - output_label) ) * ones(1, ft_no)) .* ...
            distances ./ (sigma .^2);
new_data_centers = data_centers + temp2;

new_sigma = sigma + temp2 .* distances ./ sigma;
%+++


return;
************************************************************************
% LMS FILTER INTIALIZATION (TRAINING AND TESTING)
% FIRST VERSION

% clear everything!
clear;

%loading ...:
load c:\users\ramin\fcm\multidim\ftx3;

which_features = 1:100;%------------------------to change!!!


% the data from the 'person' who is to be tested:
person = 2;
testperson = x3(which_features,person)';


polysession(1,:) = x3(which_features,1)';%nondecp
%%%[x3(81,1), x3(111,1), x3(235,1), x3(450,1), x3(452,1)];

polysession(16,:) = x3(which_features,100)';%decp
%%%[x3(81,100), x3(111,100), x3(235,100), x3(450,100),...
%%%x3(452,100)];             % polygraph data for two sessions,
                             % i.e one truthful & one decpetive

polysession(2,:) = x3(which_features,48)';%nondecp
polysession(3,:) = x3(which_features,5)';%nondecp
polysession(4,:) = x3(which_features,8)';%nondecp
polysession(5,:) = x3(which_features,9)';%nondecp
polysession(6,:) = x3(which_features,12)';%nondecp
polysession(7,:) = x3(which_features,16)';%nondecp
polysession(8,:) = x3(which_features,18)';%nondecp
polysession(9,:) = x3(which_features,21)';%nondecp
polysession(10,:) = x3(which_features,24)';%nondecp
polysession(11,:) = x3(which_features,27)';%nondecp
polysession(12,:) = x3(which_features,28)';%nondecp
polysession(13,:) = x3(which_features,32)';%nondecp
polysession(14,:) = x3(which_features,35)';%nondecp
polysession(15,:) = x3(which_features,44)';%nondecp

polysession(17,:) = x3(which_features,95)';%decp
polysession(18,:) = x3(which_features,93)';%decp
polysession(19,:) = x3(which_features,89)';%decp
polysession(20,:) = x3(which_features,88)';%decp
polysession(21,:) = x3(which_features,85)';%decp
polysession(22,:) = x3(which_features,82)';%decp
polysession(23,:) = x3(which_features,75)';%decp
polysession(24,:) = x3(which_features,72)';%decp
polysession(25,:) = x3(which_features,67)';%decp
polysession(26,:) = x3(which_features,63)';%decp
polysession(27,:) = x3(which_features,59)';%decp
polysession(28,:) = x3(which_features,58)';%decp
```

```
polysession(29,:) = x3(which_features,53)';%decp
polysession(30,:) = x3(which_features,51)';%decp
[howmany, dim] = size(polysession),% "howmany" must be even!
half = howmany/2;

clear x3;       %save memory & clear

%+++

%initialiation & clear:

step = 0.005;
output = zeros(1, 2)


output_mean = [1, 2]'

input_mean = polysession;
input_width = 1 * ones(howmany, dim);

% Testing(see 100 for des)

        [dummy, dummy, dummy, output] = ...
        adaptzzy(output_mean, input_mean, input_width, testperson,...
        100, step);
                                        % Test how good the output is at
                                        % the beginning.

end,
output
pause;

figure(1);clg
plot(output,'.');
%plot(output_mean,'.b');
hold on;
%mesh(input_width);

************************************************************************
% SEE ABOVE - SECOND VERSION.
%User interface to improve!

% INITIALIZATION:
% +++++++++++++++

step = 0.5;                             % Learning factor

% The prefix "TC" represents the input data for which the filter
% is to be (T)rained to (C)lassify:

TC_howmany = size(TC_initrain, 1);
[howmany, dim] = size(cent_initrain);      % representing data_centers

clear output;
output = zeros([TC_howmany, 1]);

% "+1" represents the nondeceptive and "-1" the deceptive data:
init_theta_non = +1 * ones(border, 1);
init_theta_dcp = -1 * ones((howmany-border), 1);

output_mean = [init_theta_non; init_theta_dcp];          %  ~ data_centers

input_mean = cent_initrain;
input_width = 100 * ones(howmany, dim);

% +++++++++++++++


% Before any training ...
% Test how good the output is at the beginning:

for k=1:TC_howmany

        if k<=TC_border
        des=+1;
        else
        des=-1;
        end

        [dummy, dummy, dummy, output(k)] = ...
        adaptzzy(output_mean, input_mean, ...
        input_width, TC_initrain(k,:),...
        des, step);

end,
clear dummy;
output,

figure(1);clg
plot(output,'+');
```

```
%plot(output_mean,'*b');
hold on;
pause;
%mesh(input_width);

% Starting training:  DO A BETTER USERINTERFACE!
for i=1:30
for j=1:5
            for k=1:TC_howmany

                        if k<=TC_border
                        des=+1;
                        else
                        des=-1;
                        end

                        [output_mean, input_mean, input_width, output(k)] = ...
                        adaptzzy(output_mean, input_mean, input_width, ...
                        TC_initrain(k,:), des, step);
            end,
end,
output,

figure(1);
plot(output,'.');               %axis([1 100 -0.2 2.1]);
%plot(output_mean,'*b');
%mesh(input_width);
%pause;

end;


%************ SAVING THE FILTER CHARACTERISTICS: ******************

fprintf('!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!\n');
fprintf('IF YOU WANT TO SAVE THE CHARACRERISTICS OF THIS FILTER,\n');
fprintf('PLEASE TYPE ANY NUMBER(#) FROM 1-99!\n');
fprintf('THIS FILTER WILL BE THEN SAVED AS "filter#" !\n');

clear numb;
numb = input('The filter number(#) is:');
% By default: numb=[], i.e. nothing will be saved.

if numb ~=[],
            numb = int2str(numb);
            com =['save ', 'filter', numb, ...
                        ' whichfeatures_3', ...
                        ' whichfeatures_2', ...
                        ' whichfeatures_1', ...
                        ' output_mean', ' output_mean', ...
                        ' input_mean', ' input_width'];
            eval(com);
end;
**********************************************************************
% CREATING THE ELLIPTICAL CLUSTERS FOR THE VISUAL
% INSPECTIONS - AND ALSO FOR STTING THE RULES.

function [x,y]=ellipse(xcenter,ycenter,xwidth,ywidth)
angle=[0:0.02*pi:2*pi];
x=xwidth .* cos(angle) + xcenter;
y=ywidth .* sin(angle) + ycenter;
plot(x,y,'-')


**********************************************************************
% TEMPORARY LMS SETTING - TEST

function output_label=fuzztemp(input_vect)
theta=[ 1 1 -1 -1]';
data_centers=[ -1 -0.5 ; 0 -0.25 ; 0 0 ; 1 0.3 ];
sigma=[ 0.5 0.8 ; 0.5 0.25 ; 0.1 0.2 ; 0.6 0.5 ];


% Get the dimensions of matrices and verify their consistency:
[label_no, ft_no] = size(data_centers);
if ([label_no, ft_no] ~= size(sigma)) | ([1, ft_no] ~=size(input_vect)) |...
  ([label_no, 1] ~= size(theta))

            error('matrix dimensions are wrong! ')
end;
%+++


% Evaluate Gaussian membershipfunctions:

distances = (ones(label_no,1) * input_vect) - data_centers;

a = exp(  -0.5 .* sum( ((distances ./ sigma) .^2 )' )'   );
```

```
% Centroidal defuzzification:
b = sum(a);
output_label = sum(theta .* a) / b;
output_label = output_label .^ 2;

return;

**********************************************************************

% LMS FILTER TESTING.
% Experimenting with the use of adaptive fuzzy logic
% in polygraph classification.

init=input('Do you want to initialize all parameters? ','s');
if init=='y'
 % Initialize the parameters for fuzzy LMS algorithm.
 % Output of 1 means nondeceptive
 % Output of -1 means deceptive
 % length(output_mean) = # of rules
 fprintf('initializing\n');
 output_mean=[ 1 1 -1 -1]';
 % input_mean=[ centers of first rule ; centers of second rule ; etc. ];
 input_mean=[ -1 -0.5 ; 0 -0.1 ; 0 0 ; 1 0.3 ];
 % input_width=[ widths of first rule ; widths of second rule ; etc. ];
 input_width=[ 0.5 1.3 ; 0.5 0.25 ; 0.1 0.2 ; 0.6 0.5 ];

 features=[451 452];          % Select the features
 step=0.005;                  % Select learning rate

 % Select training data
 ndcp_3=1:15;                 % Nondeceptive sessions in x3 for training
 dcp_3=51:65;                 % Deceptive sessions in x3 for training
 ndcp_2=[];
 dcp_2=[];
 ndcp_1=[];
 dcp_1=[];                    % Note that nondeceptive data in x1, x2, and x3
                              % are the same, so ndcp_2 and ndcp_1 are really
                              % redundant.
 load x3;
 load x2;
 load x1;
 Ntrain=[x1(features,ndcp_1) x2(features,ndcp_2) x3(features,ndcp_3)]';
 Dtrain=[x1(features,dcp_1) x2(features,dcp_2) x3(features,dcp_3)]';

 % Select testing data
 ndcp_3=[];                   % Nondeceptive sessions in x3 for testing
 dcp_3=66:100;
 ndcp_2=[];
 dcp_2=[51:100];
 ndcp_1=16:50;
 dcp_1=[51:100];              % Note that nondeceptive data in x1, x2, and x3
                              % are the same, so ndcp_2 and ndcp_1 are really
                              % redundant.

 Ntest=[x1(features,ndcp_1) x2(features,ndcp_2) x3(features,ndcp_3)]';
 Dtest=x1(features,dcp_1)';
 Dtest2=x2(features,dcp_2)';
 Dtest3=x3(features,dcp_3)';
 clear x1;
 clear x2;
 clear x3;
 clear record;
 epoch=0;
end

% Test fuzzy system before any training
% Test training data first
clear Noutput;
clear Doutput;
[Ntr,dummy]=size(Ntrain);   % Ntr = total # of nondeceptive sessions
[Dtr,dummy]=size(Dtrain);   % Dtr = total # of deceptive sessions
if Ntr ~= Dtr
        error('Number of nondeceptive and deceptive training data mismatch');
end
for i=1:Ntr
        [dummy,dummy,dummy,Noutput(i)]=adaptzzy(output_mean,input_mean,...
                    input_width,Ntrain(i,:),1,step);
        [dummy,dummy,dummy,Doutput(i)]=adaptzzy(output_mean,input_mean,...
                    input_width,Dtrain(i,:),-1,step);
end
% Record results
record(epoch+1,1:2)=[(length(find(Noutput>0))/Ntr) (length(find(Doutput<0))/Dtr) ];
squared_error(epoch+1,1:2)=[mean((1-Noutput).^2) mean((Doutput+1).^2)];
fprintf('percent correct nondeceptive and deceptive detections for training data:\n');
disp(record(epoch+1,1:2))


% Now test testing data
clear Noutput;
clear Doutput;
[Nte,dummy]=size(Ntest);    % Nte = total # of nondeceptive sessions
```

```
for i=1:Nte
            [dummy,dummy,dummy,Noutput(i)]=adaptzzy(output_mean,input_mean,...
                        input_width,Ntest(i,:),1,step);
end
[Dte,dummy]=size(Dtest);    % Dte = total # of deceptive sessions in x1
for i=1:Dte
            [dummy,dummy,dummy,Doutput(i)]=adaptzzy(output_mean,input_mean,...
                        input_width,Dtest(i,:),-1,step);
end
squared_error(epoch+1,3:4)=[mean((1-Noutput).^2) mean((Doutput+1).^2)];
record(epoch+1,3:4)=[(length(find(Noutput>0))/Nte) (length(find(Doutput<0))/Dte)];
[Dte,dummy]=size(Dtest2);   % Dte = total # of deceptive sessions in x2
clear Doutput;
for i=1:Dte
            [dummy,dummy,dummy,Doutput(i)]=adaptzzy(output_mean,input_mean,...
                        input_width,Dtest2(i,:),-1,step);
end
squared_error(epoch+1,5:6)=[mean((1-Noutput).^2) mean((Doutput+1).^2)];
record(epoch+1,5:6)=[(length(find(Noutput>0))/Nte) (length(find(Doutput<0))/Dte)];
[Dte,dummy]=size(Dtest3);   % Dte = total # of deceptive sessions in x3
clear Doutput;
for i=1:Dte
            [dummy,dummy,dummy,Doutput(i)]=adaptzzy(output_mean,input_mean,...
                        input_width,Dtest3(i,:),-1,step);
end
squared_error(epoch+1,7:8)=[mean((1-Noutput).^2) mean((Doutput+1).^2)];
record(epoch+1,7:8)=[(length(find(Noutput>0))/Nte) (length(find(Doutput<0))/Dte)];

 fprintf('training,x1,x2,x3:\n');
 disp(record(epoch+1,:))


% Start training and testing
fprintf('results after training\n')
while epoch<100000
epoch=epoch+1
clear Noutput;
clear Doutput;
 % Training
 for i=1:Ntr
            [output_mean,input_mean,input_width,Noutput(i)]=...
                        adaptzzy(output_mean,input_mean,input_width,...
                        Ntrain(i,:),1,step);
            [output_mean,input_mean,input_width,Doutput(i)]=...
                        adaptzzy(output_mean,input_mean,input_width,...
                        Dtrain(i,:),-1,step);
 end
 % end one epoch
% Test training data
 for i=1:Ntr
            [dummy,dummy,dummy,Noutput(i)]=...
                        adaptzzy(output_mean,input_mean,input_width,...
                        Ntrain(i,:),1,step);
            [dummy,dummy,dummy,Doutput(i)]=...
                        adaptzzy(output_mean,input_mean,input_width,...
                        Dtrain(i,:),-1,step);
 end
% Record results of training data at the end of an epoch
squared_error(epoch+1,1:2)=[mean((1-Noutput).^2) mean((Doutput+1).^2)];
record(epoch+1,1:2)=[(length(find(Noutput>0))/Ntr) (length(find(Doutput<0))/Dtr) ];


 % Now test testing data
clear Noutput;
clear Doutput;
[Nte,dummy]=size(Ntest);
for i=1:Nte
            [dummy,dummy,dummy,Noutput(i)]=adaptzzy(output_mean,input_mean,...
                        input_width,Ntest(i,:),1,step);
end
[Dte,dummy]=size(Dtest);
for i=1:Dte
            [dummy,dummy,dummy,Doutput(i)]=adaptzzy(output_mean,input_mean,...
                        input_width,Dtest(i,:),-1,step);
end
squared_error(epoch+1,3:4)=[mean((1-Noutput).^2) mean((Doutput+1).^2)];
record(epoch+1,3:4)=[(length(find(Noutput>0))/Nte) (length(find(Doutput<0))/Dte) ];
[Dte,dummy]=size(Dtest2);   % Dte = total # of deceptive sessions in x2
clear Doutput;
for i=1:Dte
            [dummy,dummy,dummy,Doutput(i)]=adaptzzy(output_mean,input_mean,...
                        input_width,Dtest2(i,:),-1,step);
end
squared_error(epoch+1,5:6)=[mean((1-Noutput).^2) mean((Doutput+1).^2)];
record(epoch+1,5:6)=[(length(find(Noutput>0))/Nte) (length(find(Doutput<0))/Dte)];
[Dte,dummy]=size(Dtest3);   % Dte = total # of deceptive sessions in x3
clear Doutput;
for i=1:Dte
            [dummy,dummy,dummy,Doutput(i)]=adaptzzy(output_mean,input_mean,...
                        input_width,Dtest3(i,:),-1,step);
```

```
end
squared_error(epoch+1,7:8)=[mean((1-Noutput).^2) mean((Doutput+1).^2)];
record(epoch+1,7:8)=[(length(find(Noutput>0))/Nte) (length(find(Doutput<0))/Dte)];

 fprintf('training,x1,x2,x3:\n');
 disp(record(epoch+1,:))

end          % Go to next epoch

**********************************************************************

% Experimenting with the use of adaptive fuzzy logic
% in polygraph classification.

for trial=1:1
 % Initialize the parameters for fuzzy LMS algorithm.
 % Output of 1 means nondeceptive
 % Output of -1 means deceptive
 % length(output_mean) = # of rules
 fprintf('initializing\n');
 output_mean=[ 1 1 -1 -1]';
 % input_mean=[ centers of first rule ; centers of second rule ; etc. ];
 input_mean=[ -1 -0.5 ; 0 -0.25 ; 0 0 ; 1 0.3 ];
 % input_width=[ widths of first rule ; widths of second rule ; etc. ];
 input_width=[ 0.5 0.8 ; 0.5 0.25 ; 0.1 0.2 ; 0.6 0.5 ];

 features=[451 452];        % Select the features
 step=0.005;                % Select learning rate
 trainers=10;               % Select # of training samples from each category

 % Select training data
 temp_n=randperm(50);
 temp_d=50+randperm(50);
 ndcp_3=[1:5 7:10 12 13 15 16 18:20 22 23 25 26 28 29 31 32 34 35 37 38 40 41 43 44 46:49];
 dcp_3=[51 54 57 60 64 67 70 73 76 79 82 85];% Deceptive sessions in x3 for training
 ndcp_2=[];
 dcp_2=[51 53 56 59 62 65 68 71 74 78 81 84];
 ndcp_1=[];
 dcp_1=[51 54 57 59 62 65 68 71 74 77 80 83];
                            % Note that nondeceptive data in x1, x2, and x3
                            % are the same, so ndcp_2 and ndcp_1 are really
                            % redundant.
 load x3;
 load x2;
 load x1;
 Ntrain=[x1(features,ndcp_1) x2(features,ndcp_2) x3(features,ndcp_3)]';
 Dtrain=[x1(features,dcp_1) x2(features,dcp_2) x3(features,dcp_3)]';

 % Select testing data
 ndcp_3=[6 11 14 17 21 24 27 30 33 36 39 42 45 50];
 dcp_3=[52 53 55 56 58 59 61:63 65 66 68 69 71 72 74 75 77 78 80 81 83 84 86:100];
 ndcp_2=[];
 dcp_2=[52 54 55 57 58 60 61 63 64 66 67 69 70 72 73 75:77 79 80 82 83 85:100];
 ndcp_1=[];
 dcp_1=[52 53 55 56 58 60 61 63 64 66 67 69 70 72 73 75 76 78 79 81 82 84:100];
                            % Note that nondeceptive data in x1, x2, and x3
                            % are the same, so ndcp_2 and ndcp_1 are really
                            % redundant.

 Ntest=[x1(features,ndcp_1) x2(features,ndcp_2) x3(features,ndcp_3)]';
 Dtest=[x1(features,dcp_1) x2(features,dcp_2) x3(features,dcp_3)]';
 clear x1;
 clear x2;
 clear x3;
 clear record;
 clear temp_n;
 clear temp_d;
 epoch=0;


 % Test fuzzy system before any training
 % Test training data first
 clear Noutput;
 clear Doutput;
 [Ntr,dummy]=size(Ntrain);   % Ntr = total # of nondeceptive sessions
 [Dtr,dummy]=size(Dtrain);   % Dtr = total # of deceptive sessions
 if Ntr ~= Dtr
          error('Number of nondeceptive and deceptive training data mismatch');
 end
 for i=1:Ntr
          [dummy,dummy,dummy,Noutput(i)]=adaptzzy(output_mean,input_mean,...
                     input_width,Ntrain(i,:),1,step);
          [dummy,dummy,dummy,Doutput(i)]=adaptzzy(output_mean,input_mean,...
                     input_width,Dtrain(i,:),-1,step);
 end
 %% fprintf('Results of training data before training\n');
 %% Noutput
 %% Doutput
 % Record results
 record(epoch+1,1:2)=[(length(find(Noutput>0))/Ntr) (length(find(Doutput<0))/Dtr) ];
 fprintf('percent correct nondeceptive and deceptive detections for training data:\n');
```

```
disp(record(epoch+1,1:2))

% Now test testing data
clear Noutput;
clear Doutput;
[Nte,dummy]=size(Ntest);     % Nte = total # of nondeceptive sessions
for i=1:Nte
            [dummy,dummy,dummy,Noutput(i)]=adaptzzy(output_mean,input_mean,...
                        input_width,Ntest(i,:),1,step);
end
[Dte,dummy]=size(Dtest);     % Dte = total # of deceptive sessions
for i=1:Dte
            [dummy,dummy,dummy,Doutput(i)]=adaptzzy(output_mean,input_mean,...
                        input_width,Dtest(i,:),-1,step);
end
if (Nte ~= 0) & (Dte ~= 0)
 %% fprintf('Results of testing data before training\n');
 %% Noutput
 %% Doutput
 % Record results
 record(epoch+1,3:4)=[(length(find(Noutput>0))/Nte) (length(find(Doutput<0))/Dte) ];
 fprintf('percent correct nondeceptive and deceptive detections for testing data:\n');
 disp(record(epoch+1,3:4))
end


% Start training and testing
fprintf('results after training\n')
while epoch<50
epoch=epoch+1
clear Noutput;
clear Doutput;

 % Training
 for i=1:Ntr
            [output_mean,input_mean,input_width,Noutput(i)]=...
                        adaptzzy(output_mean,input_mean,input_width,...
                        Ntrain(i,:),1,step);
            [output_mean,input_mean,input_width,Doutput(i)]=...
                        adaptzzy(output_mean,input_mean,input_width,...
                        Dtrain(i,:),-1,step);
 end
 % end one epoch
% Test training data
 for i=1:Ntr
            [dummy,dummy,dummy,Noutput(i)]=...
                        adaptzzy(output_mean,input_mean,input_width,...
                        Ntrain(i,:),1,step);
            [dummy,dummy,dummy,Doutput(i)]=...
                        adaptzzy(output_mean,input_mean,input_width,...
                        Dtrain(i,:),-1,step);
 end
%% fprintf('results of training data\n')
%% Noutput
%% Doutput
% Record results of training data at the end of an epoch
record(epoch+1,1:2)=[(length(find(Noutput>0))/Ntr) (length(find(Doutput<0))/Dtr) ];
fprintf('percent correct nondeceptive and deceptive detections for training data:\n')
disp(record(epoch+1,1:2))

if (Nte ~= 0) & (Dte ~= 0)
 % Now test testing data
 clear Noutput;
 clear Doutput;
 for i=1:Nte
            [dummy,dummy,dummy,Noutput(i)]=adaptzzy(output_mean,input_mean,...
                        input_width,Ntest(i,:),1,step);
 end
 for i=1:Dte
            [dummy,dummy,dummy,Doutput(i)]=adaptzzy(output_mean,input_mean,...
                        input_width,Dtest(i,:),-1,step);
 end
 %% fprintf('results of testing data\n')
 %% Noutput
 %% Doutput
 record(epoch+1,3:4)=[(length(find(Noutput>0))/Nte) (length(find(Doutput<0))/Dte) ];
 fprintf('percent correct nondeceptive and deceptive detections for testing data:\n')
 disp(record(epoch+1,3:4))
end
end          % Go to next epoch
maximum(trial)=max(record(:,3)+record(:,4));
temp=[find((record(:,3)+record(:,4))==maximum(trial))' 0 0 0 0 0 ];
maxima(trial,1:5)=temp(1:5);
maxima(trial,1:5)
maximum/2
end          % Go to next trial
maximum=maximum/2
```

****

EPILOGUE - Motivation, challenges and risks

I was easily fascinated by the idea of a lie-detector at the very first moment I heard about it. I thought, 'we are not supposed to lie anyway and a lie-detector can help us find and prevent a major part of the crimes committed in our society. I became even more motivated to do this research by an innovative way of pattern recognition, namely the fuzzy approach.

*But very soon, I also began to realize its danger - while juggling with **numerical data** and being far from the reality of testing actual **human beings** and judging them by an algorithm.*

*An example: **Too 'good' detection rates!***
In my project, I obtained in certain cases up to 97% correct detection rate. That is, indeed, an impressive number. However, the emphasis lies on "certain cases" - not only in this thesis.
A non-technically oriented user of such a product is tempted to put too much trust into these kinds of high rates. Even if we have a stable lie-detector with 99%(!) correct detection, this still means that one out of 100 persons will be judged incorrectly.

*In our daily life, we do not have the natural skill to "see" who is deceptive, but some biological and psychological features that enable us to estimate whether and to what degree someone is lying. This is exactly what I have exploited in this project. In fact, even the fuzzy approach is similar to the human way of categorizing someone's deceptiveness in **soft** terms like "She lies **seldom**" or "He is **often** deceptive", instead of **hard** labeling like "She **is** truthful" or "He **is** deceptive".*

After all, I am convinced that no lie-detector - even if it could work easily with different polygraph formats, and is perfect in technical terms - can ever be constructed with such a high detection rate[63] that one could judge a person without any witnesses or other additional inquiries. We may only use a lie-detector as a helpful "objective" tool, but never as an ultimate decision maker.

My initial goal was to be aware of this responsibilty and not to lose the global perspective while dealing with technical details. I hope I have accomplished this.

I also hope for an environment where we do not judge people who hurt us, but do forgive them. In that case, we ourselves are forgiven too, since all of us deserve to be judged, don't we!

Ramin Djamschidi
San Jose, September 1994.

[63] See e.g. chapter 4.3. for "Outlier effect" and "Performance limitations".

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Appendix E: Errors in the "Relevant Only" Data

NON-DECEPTIVE DATA

KEY

***standard**: CODE.011, 012, 013, 021 022, 023, 031, 032, 033

****index**: error message in MATLAB reads,

```
>>process
"Index exceeds matrix dimensions.

>>Error in==>c:\users\ulka\non\extractf.m
on line 48==> start = begin(i) + 30 .*times(first_channel,1);

>>Error in==>c:\users\ulka\non\process.m
on line 6==>feature = extractf(z, feature_list);"
```

^**read3**: CODE.01c, .02c, .03c, .023, .033, .011, .021, .031, .013
confusing as to how to READ3 these files

*****N/A**: discs were unable to be processed

^^**extra**: CODE.041, .042, .043 processed as t4

			NON-DECEPTIVE DATA			
	ERS	SUB #	CODE	# OF FILES	EXTRA FILES	ERRORS
1	1	**2**	$$EACOWO	standard*	none	none
2	1	**4**	$$EAD5LX	standard	none	none
3	1	**6**	$$EANWKF	13	0.005	none
4	1	**8**	$$EAOZD6	standard	none	none
5	1	**9**	$$EAQWB9	standard	none	none
6	1	**11**	$$EARKZ6	standard	none	none
7	1	**12**	$$EARJS0	standard	none	none
8	1	**13**	$$EA%KR9	standard	none	**index** t3**
9	1	**15**	$$EA%H#L	standard	none	none
10	1	**18**	$$EB2IYL	standard	none	none
11	1	**22**	$$EC4QN3	standard	none	none
12	1	**26**	$$EC7N7X	standard	none	none
13	1	**33**	$$ECLMTU	standard	none	none
14	1	**34**	$$ECMA%C	standard	none	none
15	1	**35**	$$ECM7GX	standard	none	none
16	1	**36**	$$ECMWB3	standard	none	none
17	1	**40**	$$EC#G2O	standard	none	none
18	1	**43**	$$EC$O0F	standard	none	none
19	1	**44**	$$ED8O5U	standard	none	none
20	1	**45**	$$ED8LUI	standard	none	none
21	1	**46**	$$ED9439	9	read3^	**N/A*** **
22	1	**47**	$$ED9TCX	standard	none	none
23	1	**50**	$$EDBQR2	standard	none	none
24	1	**53**	$$EDCZYZ	12	extra^^	none
25	1	**59**	$$EDPY4#	standard	none	none
26	1	**60**	$$EDQCY9	standard	none	none
27	1	**61**	$$EDQ28X	standard	none	none
28	1	**62**	$$EDQOCF	standard	none	**index t1**
29	1	**65**	$$EDRKGO	standard	none	none
30	1	**66**	$$EDRMU#	standard	none	none
31	2	**11a**	$$FZIMEU	13	.005, extra	**index t1a**
	2	**11b**	$$FZISQ#	standard	none	none
32	2	**12**	$$FZIT4L	standard	none	none
33	2	**14**	$$FZJ52#	standard	none	**index t1**
34	2	**30**	$$FZZN1Y	10	0.005	**index t3**
35	2	**32**	$$FZ#D6J	10	0.005	none
36	2	**33**	$$FZ#0HX	13	.005, extra	**div by zero t3**
37	2	**35**	$$FZ$3A&	standard	none	none
38	2	**36**	$$F#8CY9	11	.005,.STR	none
39	2	**38**	$$F#9FJL	10	0.005	**index t2, t3**
40	2	**41**	$$F#B6SC	standard	none	none
41	2	**42**	$$F#B6C#	standard	none	none
42	2	**45**	$$F#NMDX	standard	none	**index t1**
43	2	**47**	$$F#NHQT	standard	none	none
44	2	**48**	$$F#&7GC	standard	none	**index t3**
45	2	**51**	$$F#QJTF	standard	none	none
46	2	**52**	$$F#S0KR	standard	none	none

	ERS	SUB #	CODE	# OF FILES	EXTRA FILES	ERRORS
47	2	**53**	$$F#RRD5	standard	none	none
48	2	**54**	$$F#RYFR	12	extra	**index t3**
49	2	**55**	$$F#SALQ	10	0.005	**index t3**
50	2	**56**	$$F$C#2#	standard	none	none
51	3	**2**	$$F$D%YR	standard	none	none
52	3	**12**	$$F$I41X	11	.005,.STR	none
53	3	**25a**	$$F$IUY0	10	0.005	none
	3	**25b**	$$F$UI3X	11	.005, .STR	none
54	3	**31**	$$F$WNSF	standard	none	none
55	3	**43**	$$F%51&G	10	.STR	**index t1**
56	3	**46**	$$F%5$UF	standard	none	none
57	3	**49**	$$F%7K#0	standard	none	none
58	3	**59**	$$F%JAK6	standard	none	none

DECEPTIVE DATA

KEY

***standard**: CODE.011, 012, 013, 021 022, 023, 031, 032, 033

****Index**: error message in MATLAB reads,

>>process
"Index exceeds matrix dimensions.

>>Error in==>c:\users\ulka\non\extractf.m
on line 48==> start = begin(i) + 30 .*times(first_channel,1);

>>Error in==>c:\users\ulka\non\process.m
on line 6==>feature = extractf(z, feature_list);"

@format: files were unable to be read. Error message in DOS reads:
>format not linked
>abnormal program termination

^^extra: CODE.041, .042, .043 processed as t4

^read3: CODE.01c, .02c, .03c, .04c
confusing as to how to READ3 these files

DECEPTIVE DATA

	ERS	SUB #	CODE	# OF FILES	EXTRA FILES	ERRORS
1	1	1a	$$G3#SGD	standard*	none	index** t3a
	1	1b	$$EACLB6	standard	none	none
	1	1c	$$G3$6HN	standard	none	none
2	1	5	$$EAN#XO	standard	none	none
3	1	7	$$EAOQXV	standard	none	none
4	1	10	$$EAQ%%U	standard	none	none
5	1	14	$$EB0289	standard	none	none
6	1	16	$$EA%%MX	standard	none	none
7	1	19	$$EB2WE$	standard	none	index t3
8	1	23	$$EC4%GO	11	.005, .STR	format@
9	1	24	$$EC77GI	standard	none	none
10	1	25	$$EC76OR	standard	none	none
11	1	27	$$ECIX9#	standard	none	none
12	1	28	$$ECIVB0	standard	none	none
13	1	29	$$ECJHKO	standard	none	none
14	1	30	$$ECJVSI	standard	none	index t1, t2
15	1	31	$$ECJ#Z$	standard	none	index t3
16	1	32	$$ECLODC	standard	none	none
17	1	37	$$ECXAPG	standard	none	none
18	1	38	$$ECYCG0	standard	none	none
19	1	41	$$EC#$FA	standard	none	index t3
20	1	42	$$EC$ANC	standard	none	none
21	1	48	$$ED9$N#	standard	none	none
22	1	51	$$EDB$S3	standard	none	none
23	1	52	$$EDCSRC	standard	none	none
24	1	54	$$EDDBUX	standard	none	none
25	1	55	$$EDCBSU	standard	none	none
26	1	56	$$EDDHTI	standard	none	none
27	1	58	$$EDP26U	12	extra^^	index t1
28	1	63	$$EDQYMF	standard	none	none
29	1	64	$$EDR3XI	standard	none	none
30	1	67	$$EDS3ZL	standard	none	none
31	2	1	$$FZ3Z5S	standard	none	none
32	2	2	$$FZ3XG6	standard	none	none
33	2	5	$$FZ52G6	standard	none	none
34	2	6	$$FZ6&46	standard	none	none
35	2	8	$$FZ7B#C	standard	none	none
36	2	9	$$FZ7GP#	standard	none	none
37	2	10	$$FZIMEU	17	extra, .005, read3^	index t1
38	2	13	$$FZJ358	10	0.005	none
39	2	17	$$FZL9ZR	10	0.005	index t2
40	2	18	$$FZLBY&	standard	none	none
41	2	21	$$FZMQ#C	10	0.005	none
42	2	22	$$FZMW$H	10	0.005	index t2
43	2	25	$$FZWQQC	standard	none	index t1
44	2	26	$$FZW5T#	standard	none	none
45	2	27	$$FZYCM&	13	extra, .005	index t3

	ERS	SUB #	CODE	# OF FILES	EXTRA FILES	ERRORS
46	2	**31**	$$FZZR&C	12	extra	**index t2**
47	2	**44**	$$F#NC4B	standard	none	none
48	2	**46**	$$F#NGH3	10	0.005	none
49	2	**49**	$$F#&KWF	10	0.005	none
50	2	**50**	$$F#PUDW	standard	none	none
51	3	**14**	$$F$IK&0	standard	none	none
52	3	**16**	$$F$RJK6	standard	none	none
53	3	**36**	$$F%3C19	standard	none	none
54	3	**40**	$$F%4&C9	11	.005, .STR	none
55	3	**41**	$$F%4V0U	standard	none	none
56	3	**54**	$$F%I45#	11	.005, .STR	**index t1**
57	3	**62**	$$F%L350	standard	none	none
58	3	**66**	$$F%LXJ&	standard	none	none