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In this project, two methodolgies for evidence aggregation and information fusion were studied. One methodology uses fuzzy-set-theoretic connectives in a hierarchical network to achieve the fusion. Learning methods for determining the nature and structure of the networks are investigated. The second methodology uses a generalization of the fuzzy integral to achieve the fusion. In addition, various techniques for membership function generation (including fuzzy clustering methods), fuzzy logic inference and morphological edge detection and fusion were investigated.

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Aggregation Networks for Uncertainty Management

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Summary

Aggregation of information for decision making is frequently used in many disciplines. In this research effort, we investigated two new methodologies based on fuzzy set theory to achieve information fusion in computer vision systems. The first scheme may be described as a hierarchical fuzzy-connective-based aggregation network. The second scheme is based on the generalization of the fuzzy integral.

The proposed fuzzy-connective-based aggregation network uses degrees of satisfaction (memberships) of various decision criteria and aggregates the memberships in a hierarchical network. The nature and the parameters of the aggregation connectives are learnt through training procedures. We also presented techniques to determine the structure of such networks when this structure is only approximately known. These techniques also provide a mechanism for selecting powerful features and discarding irrelevant features via the detection of redundancies. Another attractive feature of the proposed approach is that the networks that result after training can be interpreted as a set of "rules" that may be used for decision making. This approach was tested on a variety of computer vision and automatic target recognition problems.

Robust membership generation methods are of crucial importance if the proposed methods are to work effectively. We investigated several membership generation techniques such as histogram-based methods and cluster-based methods. Although several clustering algorithms have been proposed in the literature, one major drawback of such clustering algorithms is that there is no simple way to determine the number of clusters that best describes the sample data. We devised a compatible cluster merging technique which determines the optimum number of subspace clusters in an efficient way, when an upper bound on the number of clusters present in the image or feature space is known. Our method can also be used to obtain straight-line descriptions of edge images and planar approximations of 3-D (range) data.

The second methodology that we proposed for information fusion was based on the fuzzy integral. The Fuzzy Integral is a flexible, nonlinear information fusion methodology which combines objective evidence (membership values) with expected values of subsets of the sources (as embodied in a fuzzy measure). We have extended the theoretical utility of the Sugeno fuzzy integral for information fusion. There were two extensions to this basic approach. First, we replaced the Sugeno measures by a more general class of fuzzy measures, the so-called S-decomposable measures. The second extension to the standard fuzzy integral involves the definition of the fuzzy integral itself. This is achieved by changing the max operation to one of a selected class of co-t-norms, or by replacing the min operation by one of a class of t-norms. These can either be more or less optimistic than the original fuzzy integral, giving the designer more flexibility in the design of an algorithm (or suite of algorithms) for a particular problem.

Since the process of fuzzy inference concerns the fusion of evidence - how much does the input possibility match that of the antecedent - it is only natural that flexible and powerful aggregation network structures be utilized in the inference mechanism. We generalized fuzzy inference mechanism so that a parametrically defined family of aggregation operators are used. This makes it possible for a learning algorithm to be implemented which allowed the networks to outdo the theoretically predicted performance.

Finally, we also investigated the use of morphological methods for fusing edge information from intensity and range images. Two new edge detection and classification schemes for range images based on morphological operations were developed. Several experiments involving intensity and range image pairs were conducted.

1. Introduction

In complex computer vision systems, several sensors (such as multi-spectral color sensors, range sensors, and stereo views), and several algorithms are commonly employed to reduce the uncertainty and to resolve the ambiguity present in the decisions derived from a single sensor or a single algorithm. The advantages of multi-sensor fusion lie in redundancy, complementarity, timeliness and cost of the information. Thus, there is a need for methodologies that can aggregate inexact and incomplete information obtained from multiple sources in order to make decisions. In this research effort, we addressed several aspects of the information fusion problem using fuzzy-set-theoretic approaches. A number of new theoretical results and algorithms have emerged from this research. The publications resulting from this research include five journal papers, 13 conference papers, two Ph. D. theses and two master's theses. In the following pages, we provide brief topic-wise descriptions of the major achievements of this research effort. More details may be found in the publications listed at the end of the document. The major topics addressed under this grant are:

i. Investigation of fuzzy-set-theoretic operators for information fusion

ii. Investigation of training methods to determine nature and structure of aggregation networks

iii. Elimination of redundant features/criteria and interpretation of network

iv. Methods for calculating memberships based on observed feature values

v. Experiments with aggregation networks

vi. Theoretical investigation on the generalization of the fuzzy integral

vii. Methods for calculating densities based on observed feature values

viii. Experiments with the fuzzy integral

ix. Evidence aggregation networks for fuzzy logic inference

x. Range and intensity information fusion using morphological methods

2. Investigation of Fuzzy-Set-Theoretic Operators for Information Fusion

In multi-criteria decision making, the requirements imposed by the decision-making process may be of several types. We investigated the properties of several fuzzy set theoretic aggregation operators from the point of view of flexibility and trainability. We found that fuzzy set theory provides a host of very attractive aggregation connectives for integrating membership values representing uncertain and subjective information. These connectives can be categorized into the following three classes based on their aggregation behavior: i) intersection (conjunctive) connectives, ii) union (disjunctive) connectives, and iii) compensative connectives. The intersection connective has the property that the aggregated value is high only when all of the inputs are high. The union connective has the property that the aggregated value is high whenever any one of the input values representing different features or criteria is high. Compensative connectives are used when one might be willing to sacrifice a little on one factor, provided the loss is compensated by gain in another factor. Compensative connectives can be further classified into mean (averaging) operators and hybrid operators. Mean operators are defined through an axiomatic approach. They are monotonic operators that satisfy the condition: $\min(a,b) \leq \text{mean}(a,b) \leq \max(a,b)$. Hybrid operators are defined as the weighted arithmetic or geometric mean of a pair of conventional union and intersection operators.

All these connectives are very powerful and flexible in that by choosing correct parameters, one can not only control the nature (e. g. conjunctive, disjunctive and compensative), but also the attitude (e. g. pessimistic and optimistic) of the aggregation. Our investigations indicate that Yager's union and intersection operators, the generalized mean, and the γ-model are particularly suited to model most of the aggregation behaviors that may be encountered in computer vision and artificial intelligence. We conducted thorough theoretical study of the properties of these operators. Details of the new properties discovered along with their proofs and graphical depictions may be found in [1,6,7,12,13]. Many of these properties are very interesting and useful from the point of uncertainty management.

3. Investigation of Training Methods to Determine Nature and Structure of Aggregation Networks

There are several ways to model the uncertainty management problem. In our first approach, we formulate the uncertainty management problem as a multi-criteria decision making problem as follows. The support for a decision may depend on supports for (or degrees of satisfaction of) several different criteria, and the degree of satisfaction of each criterion may in turn depend on degrees of satisfaction of other sub-criteria, and so on. Thus, the decision process can be viewed as a hierarchical network, where each node in the network "aggregates" the degree of satisfaction of a particular criterion from the observed support. The inputs to each node are the degrees of satisfaction of each of the sub-criteria, and the output is the aggregated degree of satisfaction of the criterion. Thus, the decision making problem reduces to i) selecting suitable features (criteria) for the problem on hand, ii) finding ways to compute the input supports (degrees of satisfaction of criteria) based on values of features (criteria) selected, and iii) determining the structure of the network and the nature of the connectives at each node of the network using training procedures.

We have explored several training methods based on constrained gradient descent [1,5,6,14].We have suggested methods for eliminating the constraints so that they can be viewed as simple minimization problems. Six algorithms have been developed and they may be found in [1]. Three of the algorithms are meant for single-level aggregation and the other three are for multi-level aggregation. Methods for speeding up the training procedures are also discussed. The convergence properties of the training algorithms have also been investigated. We showed that the algorithms converge to a unique (global minimum) solution under some conditions, which is a highly desirable result, particularly for gradient descent methods [1,5,6]. Our training methods determine not only the nature (disjunctive, conjunctive, compensative) of the connective to be used at each node, but also the values of the parameters (relative importance of criteria) at each node and the attitude (pessimistic, optimistic) of each node.

Gradient descent methods have the disadvantage that they may sometimes converge to a local minimum. They can also be rather slow. Therefore, we investigated alternative methods to perform the training to mitigate these problems. Our experiments with random search methods indicate that they are superior to gradient descent methods when the networks are small. For large networks, random search methods require too much memory, and their speed also goes down considerably, unless efficient ways to prune the search space are found.

4. Elimination of Redundant Features/Criteria and Interpretation of Networks

One serendipitous result that emerged from our training technique is that it is also capable of detecting redundant features (or criteria). Because of this property, we can use our training methods even though the structure of the network and the criteria to be used are only approximately known. We defined three types of redundancies. These correspond to uninformative, unreliable and superfluous criteria. Uninformative criteria are those criteria whose degrees of satisfaction are always approximately the same, regardless of the situation. Therefore, these criteria do not provide any information about the situation, thus contributing little to the decision-making process. Unreliable criteria correspond to criteria whose degrees of satisfaction do not affect the final decision. In other words, the final decision is the same for a wide range of degrees of satisfaction. Superfluous criteria are criteria which are strictly speaking not required to make the decision. The decisions made without considering such criteria may be as accurate or as reliable. However superfluous criteria may be used to make the decision-making process more robust.

A connection is considered redundant if the weight associated with it gradually approaches zero (or less than a small threshold value) as the learning proceeds. This will happen if a particular criterion is relatively unimportant in making the decision. A node (associated with a criterion) is considered redundant if all the connections from the output of this node to other nodes become redundant. In general, we found that our training procedure is capable of detecting redundancies corresponding to uninformative and unreliable criteria. Our simulations show that in both cases, the weights corresponding to all the output connections of such nodes go to zero. Therefore such nodes (criteria) are eliminated from the structure. Several examples of redundancy detection are given in [1,5,6,14]. We believe that this is one of the most powerful aspects of our approach. Another attractive feature of our approach is that the resulting networks can be interpreted as a set of "rules" that may be used for decision making. In other words, the proposed method captures an abstract model of the decision-making process.

5. Methods for Calculating Memberships Based on Observed Feature Values

One frequent criticism of fuzzy-set-theoretic methods is that the membership functions are difficult to compute. However, we developed several methods to construct membership functions from of representative training data and showed that they are effective for computer vision applications.

Fuzzy Clustering Methods: Let K denote the number of alternative decisions for which we wish to compute the relative supports (memberships) from the features. The observed feature values can be grouped into K clusters using a fuzzy clustering algorithm. The ith fuzzy cluster center is taken to be the value of the feature that best supports the ith decision if this feature value is used by itself as a criterion. These cluster centers are then be used to compute the membership value (degree of satisfaction) for each criterion for a test feature. The fuzzy K-means algorithm is straightforward and has been successfully used in our research as well as that of others in in computer vision. However, like all clustering algorithms, it can be slow, and will only work if the features exhibit natural groupings with respect to the distance measure chosen. The simple fuzzy K-means algorithm is effective only when the clusters are approximately hyperspherical and roughly of equal size. Several other fuzzy clustering algorithms exist, and the choice of the algorithm depends on the nature of the clusters one expects in a problem. In this research effort, we developed a Compatible Cluster Merging (CCM) algorithm that is specially designed to find the optimum number of linear, planar and hyperplanar clusters (i. e., clusters that lie in subspaces of the original space), when an upper bound on the number of clusters present is known. This algorithm was shown to be superior to more traditional validity-measure-based approaches. The effectiveness and advantages of the proposed technique in 2-D and 3-D applications has been demonstrated with both synthetic and real data. The proposed algorithm can be used not only for computing membership values, but also for character recognition, obtaining straight-line descriptions of intensity edge images and obtaining planar approximations of 3-D (range) data. More details may be found in [8,18].

Histogram-Based Membership Distributions: In this method, the normalized histogram from the training data is treated as a possibility distribution and the membership in each class for a particular feature value is then directly calculated using these possibility functions. One advantage of this approach is that the membership values are absolute, i. e., the membership value in one class does not depend on the membership values in the other classes. Therefore, addition of new classes to the problem can be handled easily. We successfully used this approach for membership calculation for hierarchical aggregation of TV and FLIR data for the classification of tanks and armored personnel carriers [1,6,17]. So long as the distribution of feature values for the training set is fairly characteristic of the entire ensemble, this approach will produce good membership values to be used in the aggregation scheme. While the typicality of the training samples is a concern in any pattern recognition algorithm, the power of the proposed decision-making scheme lies in the fact that the aggregation operators can be tailored to be insensitive to small variations in memberships, and in the fact that they are inherently compensatory, so that complementary and superfluous information can be used to overcome a faulty membership assignment in one feature.

Heuristic Methods: In this approach, the possibility functions are assumed to be Gaussian or trapezoidal or any other suitable shape. The membership values will be calculated using these assumed functions. The advantage of this method is that it is relatively insensitive to training data. This is a good method to use for features such as "position", "range", "speed", etc. We have successfully utilized this technique in a multi-(color)sensor fusion problem [1,6,19].

6. Experiments with Aggregation Networks

Extensive testing of the proposed techniques were conducted on both synthetic and real data.

Experiments on synthetic data: Several examples of results obtained with synthetic data are given in [1,5,6]. These include several single-level aggregation problems and multi-level aggregation problems (including the exclusive OR problem and the "stool" problems). In almost every case, the outputs produced by the networks matched the desired values very closely. Also, our training algorithms were able to perform the redundancy detection discussed in Section 4. The results of the two-class problem indicate that the performance of our method is as good as the Bayesian methods on data that is specifically designed for the Bayes method. In addition, our method is able to pick strong features and discard weak ones with no loss in performance.

Experiments on real data: Experimental results on a wide variety of problems ranging from evaluation of creditworthiness to segmentation and labeling of outdoor color scenes are described in detail in [1,5,6,17,19]. Our solution to the creditworthiness problem proved to be superior to the empirical methods used by Zimmermann [14].

Experiments on multi-modality information fusion were conducted using TV (intensity) and FLIR (forward looking infra-red) data to classify tanks and armored personnel carriers with promising results. We experimented with a variety of aggregation networks, single-level, multiple-level where the information from one modality is combined first, and multiple-level where the information from the same type of feature are combined first. These experiments are explained in [1,6,17]. A comparison of our results with those obtained by probabilistic and belief-theoretic methods indicates that our methods are superior. Results of our experiments on fusing information from three color channels are also given [6,19]. We obtained the color images from the University of Massachusetts (Hanson, Riseman et al). It is to be noted that we perform segmentation and labeling simultaneously. The results are excellent, considering the complexity of the problem. Again several types of aggregation networks were considered. One important result of these experiments are that the networks that result (after the redundancy detection process is complete) can be interpreted as a set of rules. Thus, our training methods may be used to generate decision rules.

7. Theoretical Investigation on the Generalization of the Fuzzy Integral

The fuzzy integral is another numeric-based approach which we have used for both segmentation and object recognition. It also uses a hierarchical network of evidence sources to arrive at a confidence value for a particular hypothesis or decision. The difference from the proceeding method is that besides this directly supplied objective evidence, the fuzzy integral utilizes information concerning the worth or importance of the sources in the decision making process. The fuzzy integral relies on the concept of a fuzzy measure which generalizes probability measure in that it does not require additivity, replacing it with a weaker continuity condition. The fuzzy integral is interpreted as an evaluation of object classes where the subjectivity is embedded in the fuzzy measure. In our applications, the integral is evaluated over a set of information sources (sensors, algorithms, features, etc.) and the function being integrated supplies a confidence value for a particular hypothesis or class from the standpoint of each individual source of information. In comparison with probability theory, the fuzzy integral corresponds to the concept of expectation. The fuzzy integral values provide a different measure of certainty in the classification than posterior probabilities. Since the integral evaluation need not sum to one, lack of evidence and negative evidence can be distinguished.

The Fuzzy Integral is a flexible, nonlinear information fusion methodology which combines objective evidence (membership values) with expected values of subsets of the sources (as embodied in a fuzzy measure). A particularly useful set of fuzzy measures is due to Sugeno. Our initial investigations focussed on the Sugeno integral for several reasons. First, Sugeno measures posses recursive generation properties, allowing for efficient implementation. By the structure of the fuzzy integral, it is only necessary to compute the measure on n subsets, instead of

2^n subsets, for each computation. Also, all Sugeno measures are either belief functions or plausibility functions, in the sense of Dempster-Shafer. Thus, fuzzy integrals using Sugeno measures provide a mechanism for joining fuzzy set theory and belief theory. References[5,11] describe our investigations with these techniques.

We have extended the theoretical utility of the Sugeno fuzzy integral for information fusion. There were two extensions to this basic approach. First, we replaced the Sugeno measures by a more general class of fuzzy measures, the so-called S-decomposable measures. Besides the value of generalization to a wider family of fuzzy integrals, many of these measures have generation formulae which require fewer computations than do the Sugeno measures. The algorithm using these measures of a fuzzy integral pattern recognition problem is identical to that for the Sugeno measures; the only difference being the method for generating the measures during each evaluation. In fact, even the training methods, ie, learning the fuzzy densities from labeled training data, are identical to those we developed for Sugeno measures. Only the calculation of the measure of an arbitrary subset change. Results in [2,5,15,22,23] show the extent of our research into the theory, training, and utilization of the fuzzy integral in computer vision applications.

The second extension to the standard fuzzy integral involves the definition of the fuzzy integral itself. The original fuzzy integral produced a "best pessimistic" combination of the objective evidence from knowledge sources and the worth (importance) of subsets of those sources. This is achieved by using the Maximum of a set of Minimums. By changing the Maximum to one of a selected class of co-t-norms, or by replacing the Minimum by one of a class of t-norms, many different algorithms for evidence combination can be obtained. These can either be more or less optimistic than the original fuzzy integral, giving the designer more flexibility in the design of an algorithm (or suite of algorithms) for a particular problem.

8. Methods for Calculating Densities Based on Observed Feature Values

The generation of fuzzy density values is crucial to the success of the fuzzy integral. We have developed methods to generate these density values from the histograms of the training data. These methods are based on how well separated the histograms of the same feature are for different classes. Our new method has a strong mathematical justification, and in addition, produces intuitively pleasing results [15]. In addition, for the fuzzy integral with respect to a possibility measure (a particularly nice measure from the calculational standpoint), we have introduced a density training method which performs a search in density-space for the "best" set of densities with respect a training set [16,24]. This is only possible because of the simple measure generation scheme. The details of the proposed methods can be found in [16,24].

9. Experiments with the fuzzy integral

In [2,5, 11,22,23], we developed several theoretical properties of these integrals, and examine their behavior on both simulated data, and data from multi-sensor Automatic Target Recognition (FLIR and TV). Almost all the ATR experiments that were used to test the aggregation network approach were repeated with the fuzzy integral approach. The generalized fuzzy integral in the problem of fusing information from FLIR (Forward Looking Infrared) and TV data to classify tanks and armored personnel carriers from statistical and texture features in one-, two- and three-level networks produced excellent results[11,22,23]. Comparison of our results with probabilistic and belief-theoretic methods indicates that our methods are superior. The final crisp partition is equivalent to that of aggregation networks, but the problem formalisms, the training procedures, and the interpretation of the results differ.

10. Evidence aggregation networks for fuzzy logic inference

Fuzzy logic has recently gained considerable attention. This technology has been successfully applied to numerous problems, mostly in the control area, where the complexity of the system tends to preclude an analytic solution. However, it is equally powerful in pattern recognition and multicriteria decision making environments. Fuzzy logic works well in those cases where the important decision making criteria can be expressed in terms of commonsense, linguistically-stated rules. The uncertainty in the rules is modeled numerically by fuzzy sets representing the meanings of the antecedent and consequent clauses. Once the rules have been modeled, an inference procedure is necessary to derive conclusions from uncertain conditions. Unlike predicate calculus which offers traditional modus ponens, fuzzy logic presents a multitude of inference mechanisms.

Since all rules (with common antecedent clause variables) can "fire" simultaneously in a fuzzy logic system, the computational load is considerable. Special purpose chips have been designed and built to perform particular versions of inference. Neural network structures also provide means of parallel and flexible computations. We introduced two network structures to perform fuzzy logic inference. The first type was a hand-crafted network which possessed desirable theoretical properties, whereas the second was a standard multilayer perceptron which has been shown to be capable of learning complex linguistic relationships between the antecedent and consequent of fuzzy logic rules.

Trainable evidence aggregation networks utilizing families of fuzzy set theoretic connectives have been introduced by us (Section 2) [6,7]. Since the process of fuzzy inference concerns the fusion of evidence - how much does the input possibility match that of the antecedent - it is only natural that these highly flexible and powerful network structures be utilized in the inference mechanism. Our latest activity in this area is to combine methodologies to generalize and, at the same time simplify the handcrafted networks for fuzzy logic inference. Furthermore, because of the generalization to a parametrically defined family of aggregation operators, a learning algorithm was implemented which allowed the networks to outdo the theoretically predicted performance. In [9] we proposed a fixed network architecture employing general fuzzy unions and intersections as a mechanism to implement fuzzy logic inference. It was shown that these networks possess desirable theoretical properties. Networks based on parametrized families of operators (such as Yager's union and intersection) have extra predictable properties and admit a training algorithm which produces sharper inference results than were earlier obtained. Simulation studies were presented which corroborate the theoretical properties.

10. Range and intensity information fusion using morphological methods

Range images provide an explicit encoding of the shape and the geometric structure of the objects in the image from the point of view of the sensor. Since morphological methods are inherently geometric in nature, they are ideally suited for the analysis of range images. However, morphological edge operators meant for intensity images cannot be used to detect edges in range images, because roof and crease edges do not correspond to depth discontinuities. We developed, two edge detection and classification schemes for range images based on morphological operations. The first method uses the residues of openings and closings to detect roof and crease edges. Directional sensitivity to edges is incorporated by using structuring elements oriented in different directions. The second method employs the residues of dilation and erosion at multiple scales and provides a richer description of the surface structure at each point in the image by classifying each pixel as belonging to eight possible structure types: positive roof, negative roof, positive crease, negative crease, top of step, base of step, ramp, and constant surface.

Morphological methods have the advantage of simplicity, speed and parallelism. The methods we have developed can be used for range edge detection, edge and surface characterization, segmentation of range images, and determination of hold sites in robotic applications. Several applications, including the fusion of edge information from registered range/intensity images, are described in [4,10,20,23].

Edges in intensity images occur due to changes in illumination and surface reflectance. This may or may not reflect changes in the geometry of the object. Range images on the other hand will contain edges solely due to the changes in physical shape and structure of the object. If registered intensity/range image pairs are available, then we can isolate 1) edges due to the geometric structure of the object, and 2) edges due to changes in the illumination and surface reflectance. The utility of such an approach can be seen (for example) in an application that requires that packets be picked up by a robot, and also that characters printed on the packages be read. Using intensity images alone, the changes in reflectance due to the contrast of the lettering will give rise to edges which are not hold sites for a robot arm. The range image, on the other hand can be used to determine such hold sites safely. Further, by removing these geometric edges from the intensity edge map, we can locate the lettering.

From a registered image pair denoted as *REF* (for reflectance image) and *RAN* (for range image), we obtain the edge maps, REF_{edge}, and RAN_{edge}. The problem is then to obtain 1) edges common to REF_{edge} and RAN_{edge}, 2) edges only in RAN_{edge} (geometric edges) and, 3) edges only in REF_{edge} (non-geometric edges). In order to locate all edges that are common with RAN_{edge} image, we look in a say $2n+1 \times 2n+1$ neighborhood of an edge pixel in RAN_{edge}. If we find an edge pixel in the REF_{edge} image, then we mark that pixel as a common edge, i.e., the pixel appears in the COM_{edge} image i. e., the edge image consisting of edges common to RAN_{edge} and REF_{edge}. The process of examining a $2n+1 \times 2n+1$ neighborhood of edge pixels RAN_{edge} can be accomplished by dilating the (binary) edge map RAN_{edge} by a $2n+1 \times 2n+1$ square structuring element. The resulting dilated RAN_{edge} is then ANDed with REF_{edge}.

The difference of COM_{edge} and REF_{edge} will give us the non-geometric edges (NON_GEOM_{edge}) while the difference of COM_{edge} with RAN_{egde} will give us geometric edges ($GEOM_{edge}$) not found in REF_{edge} (usually roofs, creases, and low threshold jumps, since these may not be detected in the intensity images). How the edge information contained in RAN_{egde}, REF_{edge}, COM_{edge}, $GEOM_{edge}$, and NON_GEOM_{edge} are used, depends upon the application.

11. Refefences

(Publications resulting from the work)

Ph. D. Projects:

1. "Fuzzy-Set-Theory-Based Aggregation Networks for Data Fusion and Decision Making", Ph. D. thesis, Joonwhoan Lee, August 1990.

2. H. Tahani, "The Generalized Fuzzy Integral in Computer Vision", Ph. D. Thesis, University of Missouri-Columbia, Dec. 1990.

Master's Projects:

3. "Algorithms to Detect Linear and Planar Clusters and Their Applications", Chih-Pin Freg, May 1990.

4. "Fusion of Intensity and Range Information through Morphological Feature Extraction", Sundeep Gupta, May 1991.

Journal:

5. H. Tahani and J. Keller, "Information Fusion in Computer Vision Using the Fuzzy Integral", *IEEE Transactions on Systems Man and Cybernetics*, Vol. 20, No. 3, 1990.

6. R. Krishnapuram and J. Lee, "Fuzzy-Connective-Based Hierarchical Aggregation Networks for Decision Making", to appear in *Fuzzy Sets and System*, Vol. 46, No. 3, March 1992.

7. R. Krishnapuram and J. Lee, "Fuzzy-Compensative-Connective-Based Hierarchical Networks and their Application to Computer Vision" accepted for publication in *the Journal of Neural Networks.*

8. R. Krishnapuram and C.-P. Freg, "Fitting an Unknown Number of Lines and Planes to Image Data through Compatible Cluster Merging", accepted for publication in *Pattern Recognition.*

9. J. M. Keller, R. Krishnapuram, and F. C.-H. Rhee, "Evidence Aggregation Networks for Fuzzy Logic Inference", accepted for publication in *the IEEE Transactions on Neural Networks.*

10. R. Krishnapuram and S. Gupta, "Morphological Methods for Detection and Classification of Edges in Range Images", submitted to *the Journal of Mathematical Imaging and Vision.*

11. H. Tahani and J. Keller, "The Generalized Fuzzy Integral and Its Application to Object Recognition", submitted to *IEEE Transactions on Systems, Man, and Cybernetics.*

Conference:

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