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CONDITIONED BASED MACHINERY MAINTENANCE (HELICOPTER FAULT DETECTION)

Progress Report for the Period Covering
1 July Through 31 August 1992

27 August 1992

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I. PROGRESS MADE DURING PERIOD, PROBLEMS, AND RECOMMENDATIONS

Progress

Little progress was made on the Phase I effort in the past two months. We are currently awaiting the test data set, which is expected in the very near future. Figure 1 shows the design for processing the test data set. The approach is to use the hierarchical neural network described in the previous progress report, to fuse not only a variety of features extracted from a single channel of data, but also to fuse information across sensors. As with previously described processing results, not all of the data paths indicated are likely to be required. The data and first-level network processing results will indicate which features to keep for good statistical processing performance.

The results from the first two months were used to write a conference paper (enclosed as Appendix A).

Specific progress relative to the SOW follows:

1. Identify Features and Parameters to Use

All feature extractors proposed have been developed and coded onto the ORINCON computer system. Parameters for processing will be identified when the data of interest is received.

2. Develop Feature Set Processing

Completed. Additional features will be included as they are developed on other ORINCON projects.

3. Identify Data Sets / Segments from Westland Helicopters

This task has been replaced. The government will supply the data and ORINCON will process an additional fault data set.

4. Transfer and Format Data for In-House Use

Completed for the Hollins data set, but still awaiting the test data set.

5. Process Real Data Through the Feature Extractors and Assess Utility

Not started for the test data set.

6. Develop Training Data Set

Not started for the test data set.

7. Train Neural Net

Not started for the test data set.

8. Develop Test Data Set

Not started for the test data set.

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9. Test the System

In progress for the Hollins data. Development of specific performance measures is in progress. We are currently modifying the processing to include multichannel inputs as shown in Figure 1.

10. Demonstrate the Prototype System

Not started yet.

11. Assess System Performance and Produce a Final Report

Not started yet.

12. Process an Additional Fault Detection Data Set

Not started yet. Awaiting the additional data set.

Problems

We are currently waiting for the government data that is of interest. Most of the development has been done using a system developed for an IR&D project and based on the ORINCON PRISM system. The system allows very fast training and prototype system development in trying out different signal processing parameters and feature extractors. Unfortunately, the system is incompatible with the KHOROS software recommended by the government. The outputs from the system can be made compatible with KHOROS for playback. However, some time would be required to change the software modules to the KHOROS format.

The current government-supplied data set was originally flagged in the contract as "the additional data set" (see 12 above). Thus if all the contractors are to receive this data set, we need to identify an additional data set.

Recommendations

None.

II. RESULTS RELATED TO PREVIOUSLY IDENTIFIED PROBLEM AREAS

The fire pump data has been identified as the test data set to be processed on the contract. That data set is expected to be in-house shortly.

III. DELIVERABLES COMPLETED AND DELIVERED

Completed CDRLs	Date Delivered
1. 0001AB Progress Report	August 31 1992 (this deliverable)

IV. SUBCONTRACTING AND RESULTS DURING REPORTING PERIOD

None to report at this time.

V. EXTENT OF TRAVEL

Not applicable.

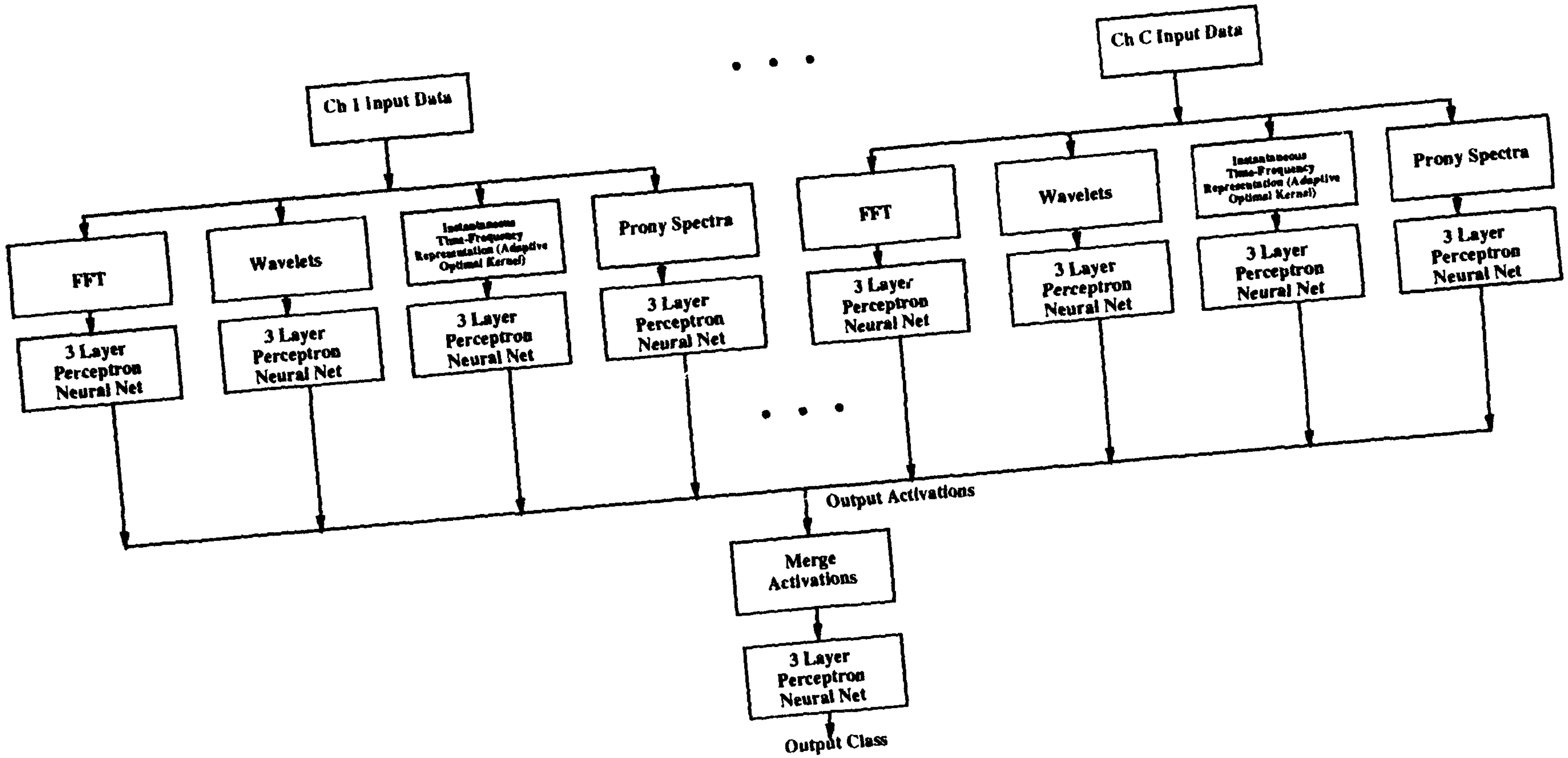

Figure 1. Test Data Set Processing

Note: To appear at the IEEE-SP International Symposium on Time-Freq. and Time-Scale Analysis, Oct. 4-6, 1992 Victoria, British Columbia

APPLICATIONS OF TIME-FREQUENCY AND TIME-SCALE REPRESENTATIONS TO FAULT DETECTION AND CLASSIFICATION

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ABSTRACT

A problem of current interest is the automatic detection and classification of faults in mechanical systems such as the gearboxes and transmissions on board helicopters. Current fault processing uses relatively simple metrics to characterize changes in measured vibration data. The metric specification and thresholds for detection and classification are found using complicated analytic models for the gearboxes. With this approach finding a solution to the problem is difficult since the understanding of the problem, the metrics that can be used, and the fault classes that are accounted for are only as good as the model developed. In many cases, the interaction of fault conditions with the mechanical system is time varying and highly nonlinear.

An alternative solution described here is to use generalized time-frequency and time-scale representations coupled with a hierarchy of neural nets. The processing assumes no underlying model for the events of interest. Rather the system 'learns' to detect and classify faults by examination and fusion of features from training data which have known fault conditions. Results of processing real helicopter gearbox vibration data with seeded faults are shown.

1. INTRODUCTION

Described here is the application of time-frequency and time-scale representations (TFRs and TSRs) for the characterization of vibration data. The TFRs and TSRs form inputs to a hierarchy of neural nets to solve for the detection and classification of faults in helicopter gear boxes and transmissions. The approach is general and can be applied to a variety of detection / classification problems. Figure 1 shows a functional flow diagram for the system considered here. The first row of boxes perform feature extraction or characterization of the input data. Feature extraction estimates a vector time series of features from the input data for a selected time segment. The feature vector forms the input retina for the multiple neural nets. The neural nets perform a mapping from the input retina - feature space to an output class. The hierarchical neural network allows for the fusion of a variety of features [1]. The approach can be expanded to include additional features as well as multiple sensors, alternative sensors, and additional classifiers. Each of the neural networks in the system has outputs that correspond to normal operation as well as a specific fault condition. The inputs to the first layer nets are the single feature extractors, while the inputs to the second layer net are the outputs from the first layer nets.

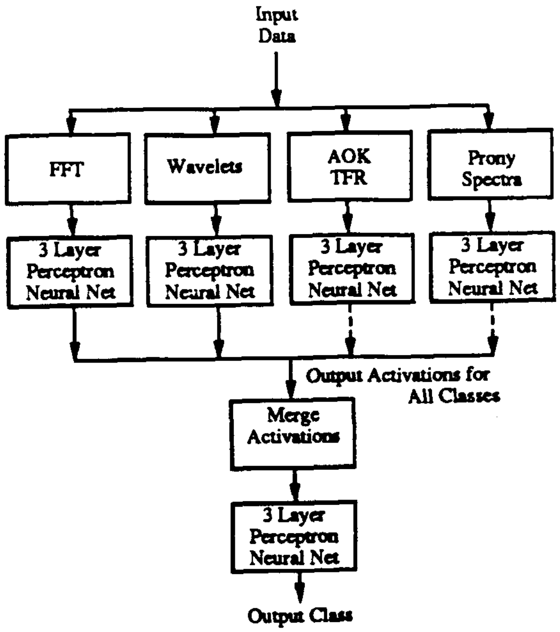

Figure 1 TFR / TSR - Hierarchical Neural Net

A problem in the design of the system is the selection of appropriate features. The goal in selecting features is to choose a set that can characterize signals of interest sufficiently so that those classes are well separated when solving the classification problem. We believe that the best "features" to use to characterize signals are not the standard scalar features that commonly are considered (such as duration, center frequency and bandwidth), but rather a compressed version of the input signal as represented by the "features" found with the TFRs and TSRs. Four techniques are considered here. They are the standard short time Fourier transform (STFT), the radially - Gaussian adaptive optimal kernel time-frequency representation (AOK TFR) [2],[3], Prony's method [4], and the wavelet transform using the Gabor wavelet [5].

Details of the feature extractors and the hierarchical neural net are given in section 2. The application of the system for fault detection / classification of real helicopter gearbox data is presented in section 3. The architecture shown in figure 1 allows for the analysis of the utility of each feature extractor. For the data set considered here the analysis indicates that the STFT and Wavelet transforms are sufficient features to resolve the different fault conditions. Section 4 contains conclusions.

2. THE PROCESSING

Details of the different system components are described here.

2.1 The STFT

The short-time fast Fourier transform (STFT) feature is found as follows: let x(t) represent the input data set; let $X_n(f)$ represent the FFT of the n-th segment of data. That is,

$$X_n(f) = \frac{1}{N}\sum_{t=0}^{N-1} w(t)\, x(nT+t)\, e^{-j\frac{2\pi f t}{N}} \tag{1}$$

where typically T = N/2 (i.e., "50% overlap") and N is a power of 2. w(t) is a window function, such as the Hamming window. The feature is a set of FFT coefficients. The set forms the feature space for any particular time/frequency segment of the input data;

$$\left\{ \log(|X_n(f)|),\, t_1 \le n \le t_2,\, f_1 \le f \le f_2 \right\}. \tag{2}$$

2.2 The AOK TFR

An instantaneous time / frequency representation (TFR) gives a high resolution characterization of the data in time as well as FFT resolutions in frequency for signals of interest. The particular TFR that we use here is the adaptive optimal radially-Gaussian kernel TFR developed by Baraniuk and Jones [2]. The TFR uses a radially-Gaussian *signal-dependent* kernel that changes shape to optimally smooth the distribution.

The optimal kernel, Φ, for a signal is defined as the solution to the following optimization problem:

$$\max_{\Phi} \int_0^{2\pi}\int_0^{\infty} |A(r,\psi)\,\Phi(r,\psi)|^2\, r\,dr\,d\psi \tag{3}$$

subject to

$$\Phi(r,\psi) = e^{-\frac{r^2}{2\sigma^2(\psi)}} \tag{4}$$

$$\frac{1}{2\pi}\int_0^{2\pi}\int_0^{\infty} |\Phi(r,\psi)|^2\, r\,dr\,d\psi \le \alpha, \quad \alpha \ge 0 \tag{5}$$

$A(r,\Psi)$ is the ambiguity function (AF) of the signal in polar coordinates. Once the optimal kernel is computed, the TFR is given by

$$P(t,\omega) = \frac{1}{2\pi}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} A(\theta,\tau)\,\Phi(\theta,\tau)\, e^{-j\theta t - j\tau\omega}\, d\theta\, d\tau \tag{6}$$

The representation is good for characterizing short duration and nonstationary events. The AOK TFR is computationally expensive. However, in the fault detection application, it is not required to run in real time. The system is only required to output detection / classification results at a relatively low rate. As with the STFT feature extractor, a time sequence of the AOK TFRs form the input retina.

2.3 Prony's Model Method

Prony's model method assumes the signals of interest are modeled by a sum of damped sinusoids. The model is well suited for characterizing impulsive type of events. The resulting model gives a variety of parameters that may be exploited in characterizing vibration waveforms. The Prony model is of the form :

$$x[n] = \sum_{k=1}^{p} A_k \exp\left[(\alpha_k + j2\pi f_k)(n-1)T + j\theta_k\right] \tag{7}$$

where $x[n]$ is the observed time series data, p is the model order, A_k is the amplitude of the k-th coefficient, α_k is the corresponding damping term, f_k is the center frequency, T is the sample interval, and θ_k is the initial phase. The parameters of the model can be estimated using least squares techniques [4]. Several different noise discrimination techniques have been developed for use with the Prony model method [6]. In the processing presented here a time sequence of spectral estimates derived from Prony's model fit to the data is used.

2.4 Wavelet Processing

The wavelet transform (WT) is a time domain representation of a signal in terms of dilated and shifted versions of suitable analyzing wavelets. Here we use a discrete approximation of the continuous wavelet transform. The analyzing wavelet used is the analytic portion of the Gabor function;

$$h(t) = \sin(\omega_0 t)\left[\frac{1}{\sqrt{2\pi}\sigma}\exp\left(\frac{-t^2}{2\sigma^2}\right)\right]. \tag{8}$$

A time sequence of wavelet transforms forms the input feature space to the hierarchical neural net classifier.

2.5 Hierarchical Neural Net Processing

The feature sets are input to the hierarchical neural net for detection and classification processing. The hierarchical net shown in figure 1 has been successfully used to fuse multiple features together so as to increase the probability of detection and correct classification while at the same time reducing the probability of false alarm [1] Here each neural net is a three layer perceptron. The first layer of nets process the single feature vectors . The output from the first layer of nets is then input to a second layer to 'fuse' the results from the first layer together. For the hierarchical multi-network architecture, single-feature exemplars are selected and used to train the set of four single-feature neural networks independently. To finish the training of the hierarchical multi-network architecture, each of the *trained* single feature neural nets are run on the *training* data. The various outputs from the single feature neural networks are aggregated together to form the input to the hierarchical neural network as shown in Figure 1. A second exemplar selection is performed for training of the second layer net.

3. REAL DATA PROCESSING RESULTS

The data set used was collected by Mark Hollins of the Naval Air Test Center. It consists of vibration data from the tail rotor transmission of a TH-1L helicopter. Data for normal and five induced faults conditions were collected. Initially the four feature extractors described were considered. Table I shows the parameter settings used. For the results described a detailed investigation of the feature extraction parameters was not made. The only parameter adjusted was the time duration (or extent) of the input retina to the fusion network of the hierarchical network.

Each of the neural networks used is a three layer perceptron. Training is performed until the RMS training error from each of the networks is approximately 0.01. In past work at ORINCON this RMS error has resulted in networks that give robust detection / classification performance for both training and test data sets. Visual inspection of the single feature network outputs on test data resulted in the AOK TFR and Prony model spectra being dropped from the fusion network processing (i.e. the dotted lines in figure 1 show connections that were initially considered but are not included in the final system described here). It is important to note that these results only apply to the Hollins data set and may not hold for additional data sets.

Figure 2 show specific results for the 'bearing outer race fault' class category for the Hollins data set. There are five separate windows in the display shown in the figure. The windows labeled 'fft', 'prony', 'AOK', and 'WAVELET' correspond to individual feature extractors as well as the output activations from the single feature networks (see the 'Prony' window in figure 2). The network activations correspond to:

Column 5 = Normal gearbox,
Column 0 = Bearing inner race fault,
Column 1 = Bearing rolling element fault,
Column 2 = Bearing outer race fault,
Column 3 = Gear spall fault and,
Column 4 = Gear 1/2 tooth cut fault.

The neural net outputs are intensity encoded (the real system uses color / temperature encoding). Dark values indicate a relatively low activation level. White indicate a relatively high activation level. The feature extractors show the same amount (or time duration) of data, however each extractor uses different processing parameters so that the output scan rates are different. For example for the 'prony' and 'WAVELET' feature extractors there are four output scans for each output scan of the 'fft' extractor. The 'AOK' extractor outputs eight scans for each of the 'fft' extractor.

The window labeled 'fusion_net' shows the inputs and the output for the second layer net in the hierarchical neural net. The input features are the outputs from the FFT and Wavelet first layer networks as shown in figure 1. The FFT output from the first layer have been stretched in time so as to synchronize with the faster running Wavelet feature extractor. The figure shows results for processing of test data that contains only the event of interest.

Each of the extractors gives a different spectral representation of the data. The ideal neural net performance would result in the column corresponding to the gearbox condition being bright white when data for that condition is input to the system and black for the other fault conditions. For example in figure 2 the third column over (labeled column 2) should be bright white while all the other columns should be dark for perfect processing. Drop outs in the 'Normal gearbox' class column or activations in other columns correspond to false alarms with in the system when no-fault data is input. Low or no activations for the event of interest column, when the event is present, corresponds to missed detections or missclassifications. As seen, for all of the single feature nets there are significant dropouts and missclassifications. The Prony and AOK TFR nets give the poorest performance. The FFT and Wavelet nets performance are still far from ideal. However, the output from the fusion net is close to ideal. Figures similar to that shown in 2 for both normal and other fault conditions give equally good results.

The fusion net uses a fairly long integration time (200 scans which is about 1/3 the length of the display shown in the fusion net). Long integration times (i.e. retinas with long time extent) are possible with the second net in the hierarchical network. This is because there are relatively few inputs to the network (here there are only 12 inputs to the second layer network). The first layer nets are restricted to have short time extent (unless averaging of time scans is performed). This is because a scan is typically made up of 128 or 256 points so that large numbers of scans are not computationally tractable.

4. CONCLUSIONS

We have shown that the use of multiple TFRs and TSRs coupled with a hierarchical neural net approach appears to work well for characterization, detection, and classification of faults from vibration data in mechanical systems. The results indicate that only the FFT and Wavelet feature extractors are required for detection and classification in the Hollins data set. The parameters that we have selected result in single feature retinas that cover half to a full rotation of the gearbox shaft. Multiple revolutions are integrated together in the second layer of the hierarchical net. Further investigation of the parameters used in the single feature extractors is required to develop processing to identify alternative fault conditions.

The approach described is general and can be applied to a variety of problems; it has has been applied to underwater acoustic problems and diagnosis of blood flow from ultra sound measurements with equal success. The hierarchical neural net can also be used as a tool for the analysis of the utility of individual feature extractors for solution of the detection / classification problem. In addition to the problem described here, the hierarchical neural net can be used to fuse multiple sensors, alternative sensors, as well as different classifiers.

REFERENCES

[1] T.W.Brotherton, D.Fogel, and E.Mears, Final Report for Applications of Data Fusion to Signal Processing DARPA Phase I SBIR, The ORINCON Corp, March 1992
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[3] R.G.Baraniuk, D.L.Jones, T.W.Brotherton, and S.L.Marple, Applications of Adaptive Time - Frequency Representations to Underwater Acoustic Signal Processing, *25th Asilomar Conference on Signals, Systems & Computers*, Pacific Grove CA, Nov. 1991
[4] S.L.Marple, *Digital Spectral Analysis with Applications*, Prentice-Hall, 1987
[5] Rioul, O. and Vetterli, M. (1991), "Wavelets and signal processing," IEEE Signal Processing Mag., Oct. 1991.
[6] S.L.Marple and T.W.Brotherton, Detection and Classification of Short Duration Underwater Acoustic Signals by Prony's Method, *IEEE ICASSP '91*, May 1991.

FFT	Wavelet	AOK TFR	Prony's Method	Fusion Net
Window Size = 256 FFT Size = 256 Window = Hamming Samples Skipped = 128 Retina : 5 Time Scans x 60 Frequency Bins (bins 2 - 62)	Analyzing Wavelet = Gabor No. of Scale Factors = 71 Low Bin Center Freq. = 768 Hz High Bin Center Freq. = 16642.56 Samples Skipped = 32 Retina : 10 Time Scans 71 Frequency Bins	Window Size = 128 FFT Size = 256 Kernel : Volume = 2.5 No. Grad. Steps = 6 Samples Skipped = 16 Retina : 20 Time Scans x 60 Frequency Bins (bins 2 - 62)	Window Size = 64 Model Order = 12 FFT Size = 256 Samples Skipped = 32 Retina : 10 Time Scans x 60 Frequency Bins (bins 2 - 62)	Retina : 200 Time Scans x 12 Inputs

Table I. Parameter Settings

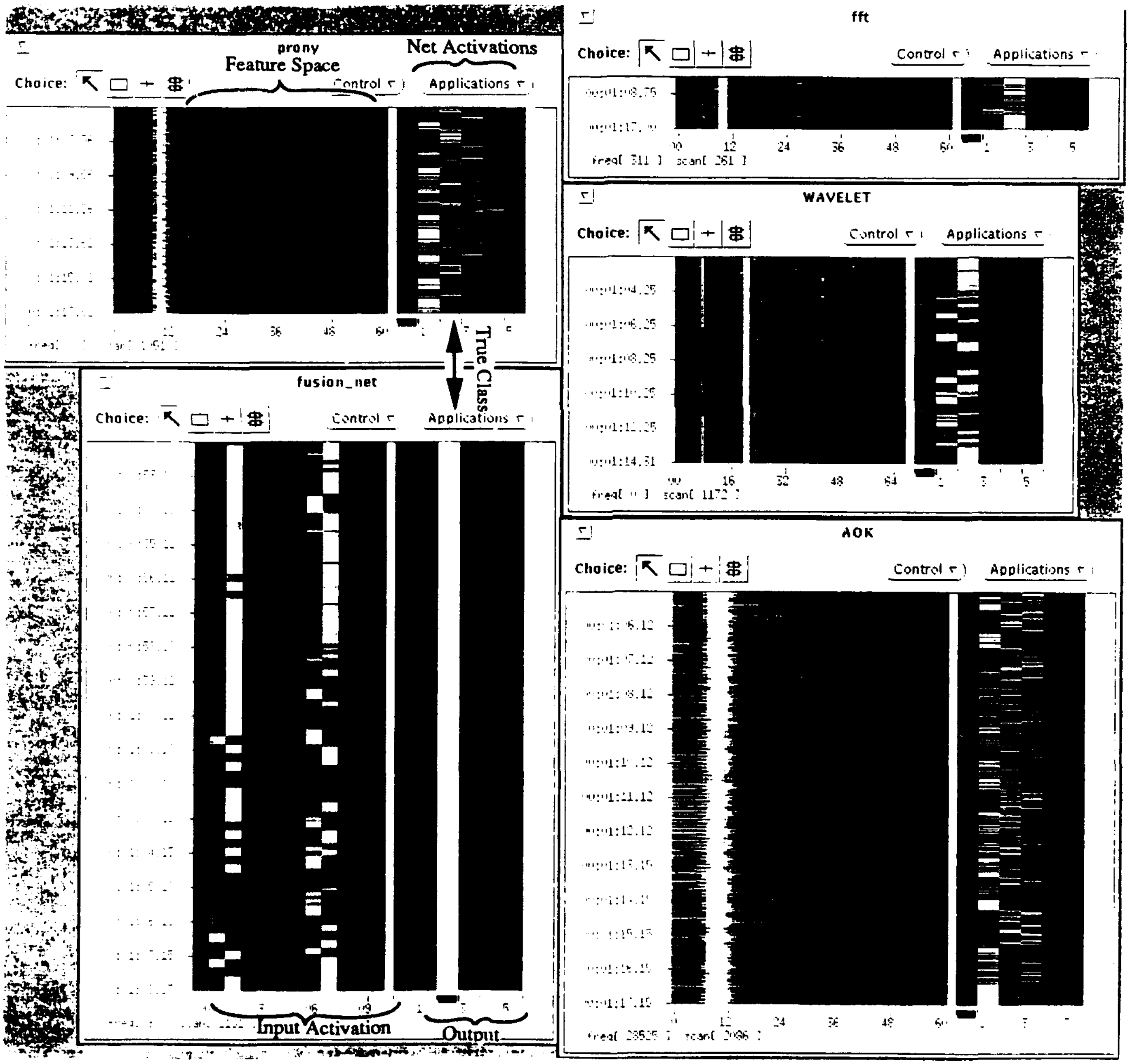

Figure 2. Fault Detection Processing Example : Bearing Outer Race Fault

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