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Application of sensor fusion and signal classification techniques in a distributed machinery condition monitoring system

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ABSTRACT

A new paradigm for machinery maintenance is emerging as preventive maintenance strategies are being replaced by condition-based maintenance. In condition-based maintenance, machinery is repaired or serviced only when an intelligent monitoring system indicates that the system cannot fulfill mission requirements. The implementation of such systems requires a combination of sensor data fusion, feature extraction, classification, and prediction algorithms. In addition, new system architectures are being developed to facilitate the reduction of wide bandwidth sensor data to concise predictions of ability of the system to complete its current mission or future missions. This paper describes the system architecture, data fusion, and classification algorithms employed in a distributed, wireless bearing and gear health monitoring system. The role and integration of prognostic algorithms – required to predict future system health - are also discussed. Examples are provided which illustrate the application of the system architecture and algorithms to data collected on a machinery diagnostics test bed at the Applied Research Laboratory at The Pennsylvania State University.

Keywords: Machinery condition monitoring, data fusion, pattern recognition, fuzzy logic

1. INTRODUCTION

Traditional time-based machinery maintenance is being replaced by maintenance based on the condition of the machinery. Under condition-based maintenance, parts and components are replaced only when they can no longer operate at the desired capacity or load, or when the machine will not be able to operate long enough to complete its current mission. Mission examples include traditional military definitions for aircraft, ships or other vehicles, a shift or product run for factory equipment, a family vacation for an automobile, or even an unspecified length of time for other devices such as a pacemaker or artificial organ.

Automated machinery diagnostics promises millions of dollars in cost savings per year in the form of decreased machinery downtime, unnecessary replacement of "good" parts and components, and maintenance-induced failures. The key to the successful implementation of condition-based maintenance strategies is the accurate diagnosis of existing component faults, and the ability to predict when components are going to fail. The latter is the real the key to successful condition-based maintenance, since we need to know that a part is going to fail during the next mission before we put the machine into service. We must be able to reliably predict when components are going to fail, and furthermore, we must develop analysis techniques that can be implemented on embedded processing systems to automatically identify the remaining useful life of components, without intervention from a human expert.

It is well known that the vibration produced by gearboxes contains important diagnostic and prognostic information about to the operating condition of the gears within it. Over the past two decades, many signal-processing techniques have been proposed to extract this information from gearbox vibration signals. The most popular of these signal-processing techniques have included various statistical parameters, time-domain averaging, amplitude and phase demodulation, time-frequency techniques and most recently wavelet analysis. In most cases, however, determining the operating condition and predicting

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the remaining useful life for a machine requires more than the calculation of a single feature. The implementation of such systems requires a combination of sensor data fusion, feature extraction, classification, and prediction algorithms.

2. SYSTEM ARCHITECTURE

The Applied Research Laboratory has been working with a team of industrial, university and government partners to develop and demonstrate the physical devices, system architectures, algorithms, and processing techniques required to implement condition based maintenance. A three-layer, hierarchical architecture has been developed and demonstrated for use in machinery health monitoring system. Figure 1 shows the three primary layers within the architecture.

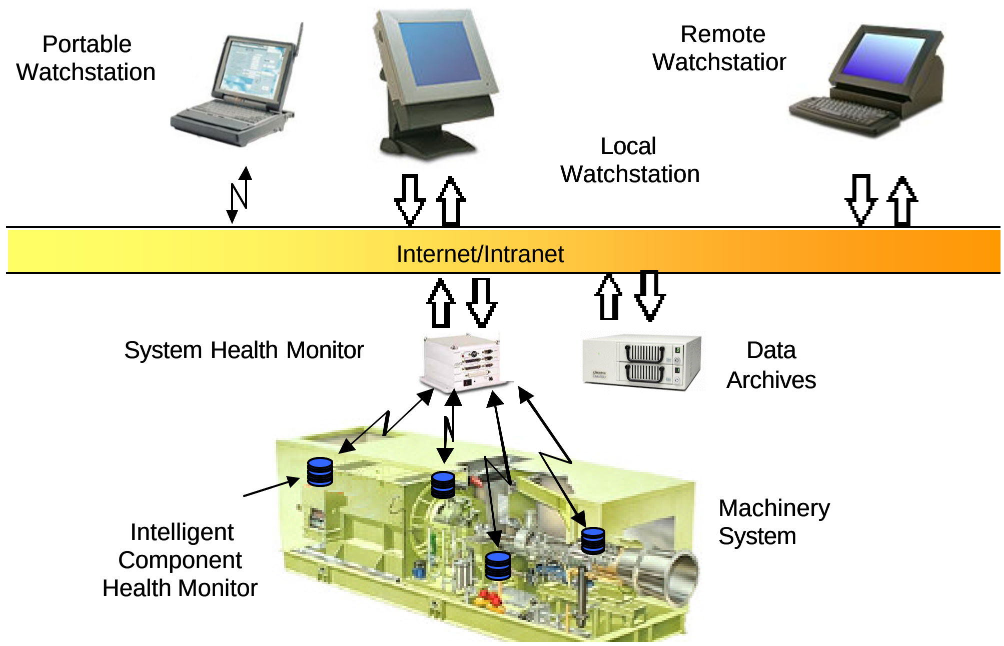

Figure 1. Three-layer condition monitoring system architecture.

The lowest level is composed of Integrated Component Health monitors. These are effectively smart sensors capable of acquiring data, extracting features, and performing sensor-level data fusion and pattern recognition. The integrated component health monitors are intended to monitor a single component on a machine such as a bearing, gear or gearbox, compressor or electric motor. By processing the sensor data at the sensor, we can minimize the need to send raw data from the sensors to the monitoring station. In general, the integrated component health monitors are designed to be low power and use wireless communications – it would be self-defeating to develop a condition based maintenance system that replaces scheduled maintenance of the machine with scheduled battery replacement and unreliable wiring.

At the next layer in the network, System Health Monitors collect information from several component health monitors. The system health monitor has a wider view of the world, which may include mission-oriented information and is in a better position to interpret the impact of the information from the sensors than the component health monitors. While a component health monitor could perform both the system and component health monitor roles and vice-versa, dividing the responsibility between the two levels may permit a more cost effective implementation. With wireless connections between the system and component health monitors, the system health monitor hardware may not be required to meet the same environmental operating specifications as the sensor. Likewise, we can reduce the cost of the component health monitor by minimizing the amount of information about system operating set points and mission requirements that is downloaded to the component health monitor. The system health monitor communicates with the upper levels of the system via the Internet, a local area network, or some form of intranet. The system health monitor may include archival storage or may utilize archival storage capability on the Internet or intranet.

The highest level of the network coordinates and fuses the information from different system health monitors and provides a connection for human user interfaces to the system. The platform level monitor has the most global view of the platform or plant and provides the opportunity for user input and mission profile changes. The functional requirements for the architecture are designed to permit drill-down from the platform level as well as changes in the algorithms and methods used to analyze data throughout the layers of the architecture.

3. DATA FUSION AND PATTERN RECOGNITION

The primary goal of developing a multi-level architecture is to increase the information content and decrease the required communication bandwidth as one moves up in the condition monitoring system away from the sensors and machine toward the user. For systems where the quantities being monitored are slowly changing temperatures, the bandwidth required to send raw data to the highest level in the network are small, however, if the quantities being monitored are vibrations, the bandwidth of the raw data could be in the 100's of kHz range. Figure 2 shows the transformation of raw sensor data from sensor-oriented data to condition-oriented information in the condition monitoring system. At the left in Figure 2 are the component health monitors and at the right is the platform-level monitor.

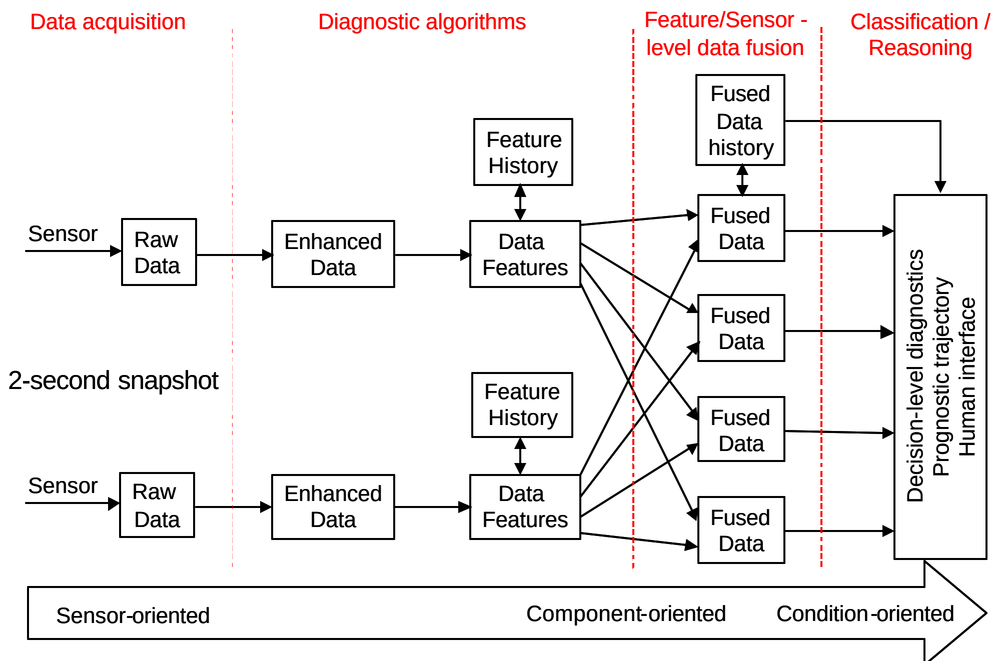

Figure 2. Data reduction in condition monitoring system.

Figure 2 shows the processing flow for a generic machinery condition monitoring system. At the sensor or component monitoring level, raw data is processed to enhance signal to noise ratio and remove unwanted signal components. Two common techniques are frequency banding and time-domain averaging. Bearing defects may excite structural resonance frequencies in a mechanical system, which effectively amplifies the impulsive, or random vibration energy. Frequency banding helps to isolate regions of the frequency spectrum where bearing defect vibration energy is "favored". Time domain averaging over the revolution period of a specific shaft isolates gear mesh effects from that shaft. Time-synchronous averaging is often implemented using triggered data sampling where a tachometer signal is used to align multiple shaft periods for averaging.

Data fusion techniques are used at the sensor level to insure data quality and provide for sensor self check [2]. It is very important in condition monitoring systems to avoid the introduction of unreliable sensors that would cause false alarms. Moreover, sensors are being developed that are capable of measuring multiple physical quantities, such as vibration and temperature. By fusing the information from several measurands or from multiple commensurate sensors we can improve sensor and data reliability.

The next step in processing the sensor data is feature extraction. Features may be statistical characteristics of the electrical signal produced by a sensor or may be based on some physical characteristic of the system. A wide range of feature extraction techniques have been developed and applied to the monitoring of vibrations from gears and bearings. Statistical features include RMS level, peak level, skewness, and kurtosis. Frequency domain features include the frequency and magnitude of spectral peaks from frequency band enveloping, characteristic defect frequencies, harmonics, and sidebands, modulation frequencies, strength and patterns, and frequency band and broadband energy levels.

Because computational resources are limited at the component monitoring level and we want to minimize the amount of data that is sent from the component level to the system health monitor, we must carefully choose the feature extraction algorithms that are implemented at the component health monitoring level. The ideal situation would be to find or develop a feature extraction technique that produced a single feature that ranged from 0 to 1 and progressed linearly from "good" to end of life. Since this is the real world, however, such a feature rarely exists and we must use additional data fusion and pattern recognition techniques to determine the component health from multiple features. An addition consideration, however, is our ability to track and predict the future values of the features we calculate if we want to perform prognostics instead of just diagnostics [3].

The problem of determining the health of a system from several computed features is essentially a pattern recognition problem. Pattern recognition approaches can be broadly characterized as statistical, syntactic, or neural [4]. We have chosen to use a syntactic or rule-based approach in some of the machinery condition monitoring applications. The rule-based classifier uses fuzzy logic to combine features and compute a confidence in the existence of a particular fault condition.

Figure 3 shows a block diagram of a fuzzy-logic classifier for determining the health of a roller bearing. The inputs to the classifier are features computed using multiple analysis tools. The features are then blended, weighted, and combined using logical rules. The blending process, also referred to as fuzzification, in the fuzzy-logic literature maps numerical outputs of the feature extraction techniques to subjective levels of severity [5]. For example, the frequency band RMS level is transformed from a number to a confidence in an observation such as "the RMS level is high".

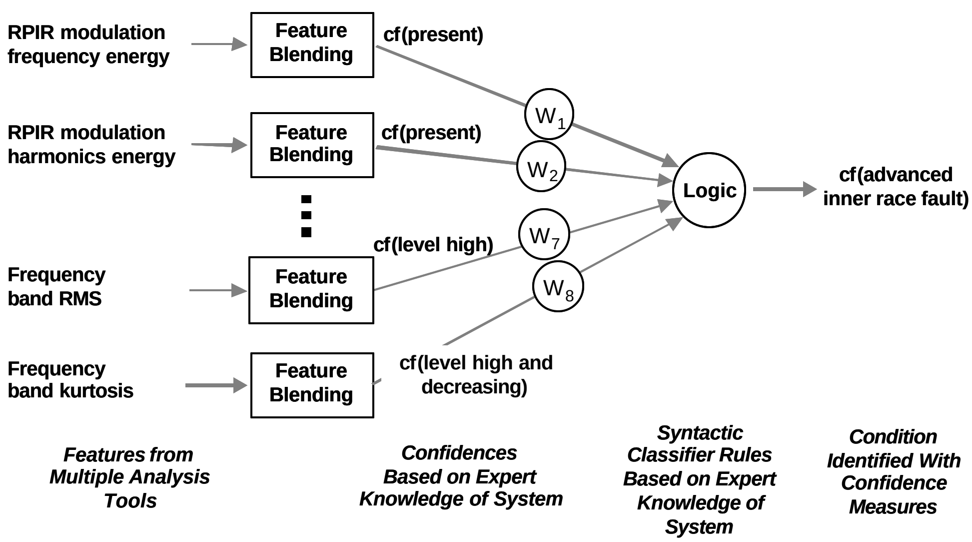

Figure 3. Fuzzy-logic classifier for roller bearing fault classification.

After blending, the feature confidences are weighted by relative importance and combined using a rule to determine the overall state of the component. For example, the rule for determining whether a bearing has an advanced inner race fault condition might take the following form:

Bearing has an advanced inner race fault if
RPIR modulation frequency energy is present AND
RPIR modulation harmonic energy is present AND
Frequency band RMS energy is high AND
Frequency band kurtosis is high OR
Frequency band kurtosis was previously high and now decreasing.

These types of rules are typically developed based on expert knowledge of the system.

4. TRACKING AND PREDICTION

The goal for condition based maintenance systems is not simply automated diagnosis of machinery fault conditions, but determination of the remaining useful life of the system within the context of the current mission. As such, the system must have prognostic as well as diagnostic capability. Using a model-based approach, the system could simply take the current machine state invert the model to compute the effective remaining useful life. In the absence of a reliable or accurate system model, however, another approach is to determine the remaining useful life by monitoring the trajectory of a developing fault, and predicting the amount of time until the developing fault reaches a predetermined level requiring action. This problem is analogous to computing time -to-intercept in an object-tracking problem.

Two well-known tracking/prediction techniques have been applied to vibration data from the gearbox: the Alpha-Beta-Gamma tracking filter and the Kalman filter [3]. The tracking and prediction techniques have been applied to a number of traditional vibration-based diagnostic features as well as new features developed under the current research program [6-7]. It is assumed that the measurements and system model are noisy. Both the Alpha-Beta-Gamma and the Kalman tracking filters have been investigated for their ability to track and smooth features from gearbox vibration data. A Kalman tracking filter has been used to predict the feature trajectory of feature states as damage progresses in the mechanical system. The feature "state vector" is defined as a vector containing the current feature value, the first derivative of the feature value with respect to time, and the second derivative of the feature value with respect to time. These correspond to the position, velocity, and acceleration of the feature. The estimated position, velocity, and acceleration can then be used to estimate the remaining useful life of the system by predicting when the system will reach a damage state that will no longer permit safe operation.

A feature based on the total signal energy was used to predict the remaining useful life for a commercial gearbox during a run-to-failure test conducted on a test stand at Penn State. Around 17 hours into the test, the predicted remaining useful life converges to the actual time left in the test. After converging at 17 hours, the prediction of the remaining useful life remains accurate through the end of the test. Several different methods are still under investigation for improving the calculation of the remaining useful life for a component.

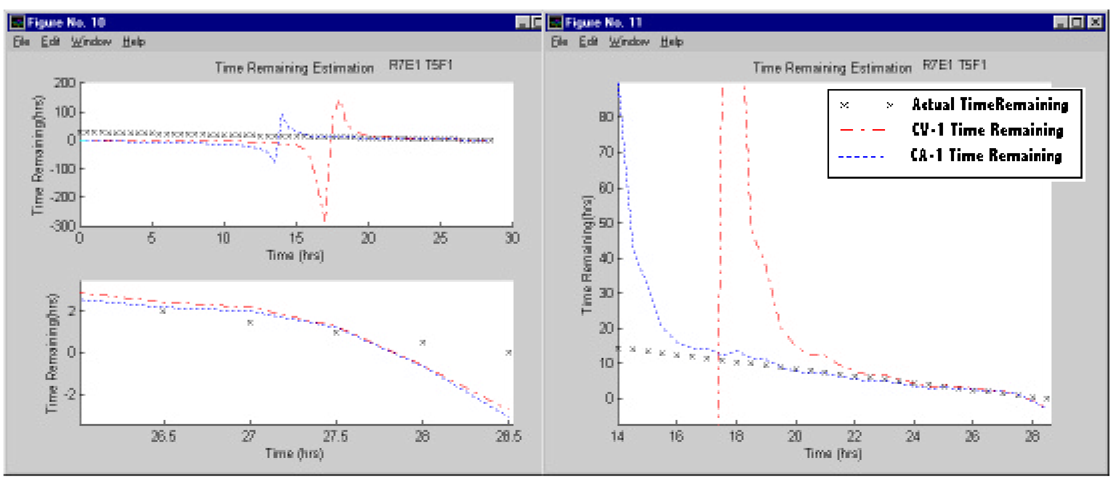

Figure 4. Time Remaining In Event Estimation. From top to bottom, left to right: 1) The estimation results for each of the methods and the actual time remaining ; 2) The estimation during the last 10% of the event; 3) Estimation results during the last 14 hours of the test.

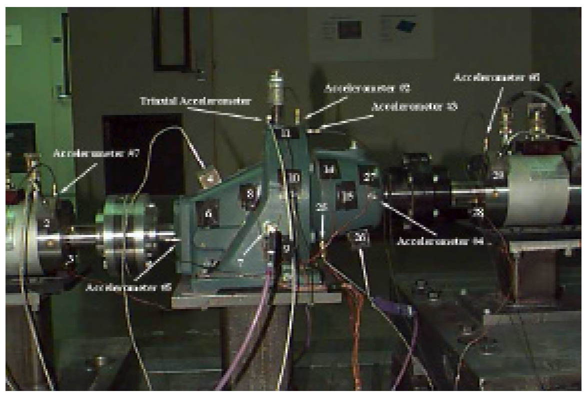

Figure 5. Instrumented gearbox on the ARL/PSU machinery diagnostics testbed.

it is possible to have nonzero confidence in the notion that the value is both low and medium or medium and high.

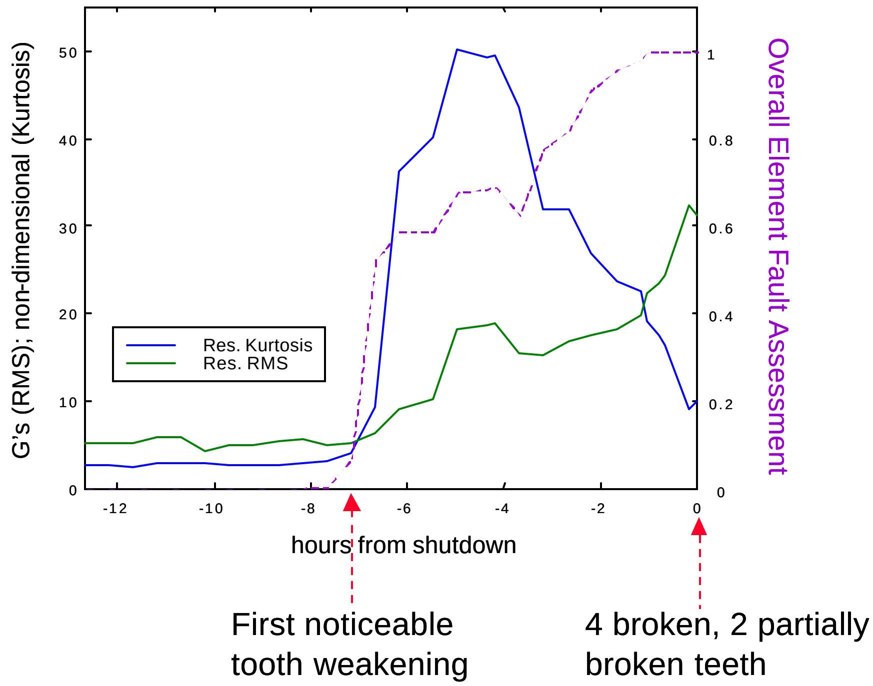

Figure 6. Classification results for gear monitoring.

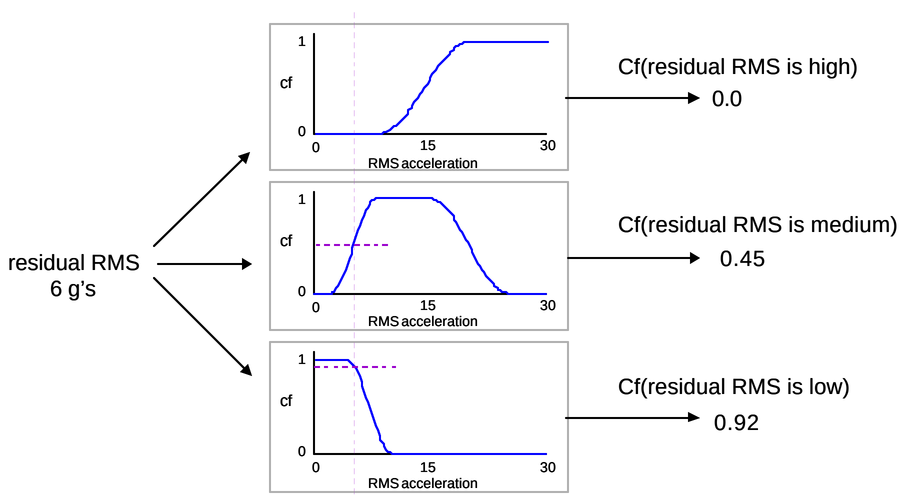

Figure 7. Fuzzy-logic blend process for residual RMS feature.

CONCLUSIONS

A new condition-based approach to machinery maintenance is emerging in which machinery is repaired or serviced only when an intelligent monitoring system indicates that the system cannot fulfill mission requirements. The implementation of such systems requires a combination of sensor data fusion, feature extraction, classification, and prediction algorithms. In addition, new system architectures are being developed to facilitate the reduction of wide bandwidth sensor data to concise predictions of ability of the system to complete its current mission or future missions. In this paper we have described a three-layer architecture for monitoring mechanical systems with smart sensors at the lowest level, system level monitors at the middle level capable of performing data fusion and pattern recognition, and a platform-level monitor at the highest level to provide a user interface and pass platform and mission requirements down to the system monitoring level. Machinery monitoring requires data fusion, pattern recognition, tracking, and prediction algorithms in order to determine the remaining useful life for a piece of machinery. Example results from a commercial gearbox mounted on an experimental test stand at Penn State were presented that demonstrate the use of these techniques to determine the condition of the system. The integration of prediction and tracking with the diagnostic pattern recognition techniques is ongoing.

ACKNOWLEDGEMENTS

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REFERENCES

1. Byington, C.S., Kozlowski, J.D., "Transitional Data for Estimation of Gearbox Remaining Useful Life", 51st Meeting of the Society for Machinery Failure Prevention Technology (MFPT), April 1997.
2. Hall, D.L., *Mathematical Techniques in Multisensor Data Fusion*, Artech House, Inc., Norwood, MA, 1992.
3. McClintic, K., *Feature Prediction and Tracking for Monitoring the Condition of Complex Mechanical Systems*, The Pennsylvania State University, MS Thesis, PA, 1998.
4. Schalkoff, R., *Pattern Recognition: Statistical, Structural and Neural Approaches*, John Wiley & Sons, Inc., New York, NY, 1992.
5. Gibson, R.E., Hall, D.L., and Stover, J.A., "An Autonomous Fuzzy Logic Architecture for Multisensor Data *Proceedings of the 1994 IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems*, 143-150.
6. Ferlez, R.J, Lang, D.C., "Gear-Tooth Fault Detection and Tracking Using the Wavelet Transform," 52nd Meeting of the MFPT , Mar 30-Apr2, 1998.
7. Maynard, K. P., "Interstitial Processing: The Application of Noise Processing to Gear Fault Detection," International Conference on Condition Monitoring, University of Wales Swansea, April 12-15, 1999, p. 77-86