Unsupervised Rule Generation for Maintenance of a Diagnostic System

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Abstract

A common limitation of diagnostic systems is their dependence on the training data. It is essential that the diagnostic system should be maintainable over time. In most practical applications the data used for training a diagnostic system does not cover the entire spectrum of faults that a system could encounter. Thus the system should be able to generate rules for new "unknown" faults. An effective methodology for a minimally supervised diagnostic system is developed and explained in this paper. Fuzzy logic is used for automatic generation and evolution of rules, based on the extracted feature set, for detection and identification of new faults

Introduction

The detection and identification of faults in a system or process involves tasks associated with system identification, trending analysis, and classification. The deviation of the parameter values from the normal operational values and bounds of the system characterize the faults. Faults can possibly be effected because of several reasons. The faults are detected in a system by observing either the state space model of the system or from other data sources, such as images, error logs, or sensor readings. It is important to detect and identify the failure condition and take corrective action.

A major challenge in the servicing industry is to develop algorithms for monitoring, and fault detection and identification products and processes. Several Artificial Intelligence techniques have been implemented for various industrial applications, such as neuro-fuzzy approach for fault diagnosis in dynamic systems (Caminhas, Tavares, and Gomide 1996), fuzzy logic control applied to automotive idle speed control (Vachtsevanos, Farinwata, and Kang 1992).

Neural Networks also have been successfully applied to a number of power engineering classification problems. Neural Networks have been used to differentiate between high-impedance and other transient events (Ebron, Lubkeman, White 1990). In this study, a number of training cases for a typical 12KV distribution system were developed through the use of Electromagnetic Transients Program (EMTP). Backpropagation learning algorithm was then applied to train the network. The results indicated that this type of supervised approach could be applied.

Unfortunately, in industrial applications it is impossible to cover the entire fault space while training and developing the diagnostic system. In addition, training data needs to be real process data and simulation data cannot be used to train the system. Hence, a more desirable approach to develop a classification system would be to utilize the unsupervised learning and automatic rule generation for implementing a diagnostic system, which learns and evolves, as new information becomes available.

A number of papers have been written on Automatic Rule Generation for fuzzy controllers using genetic algorithms, (Hyun-Joon, Wang, Roychowdhowdhury, 1998), and Automatic Rule Generation for hierarchical fuzzy systems (Holve, 1998) but these methods are limited by the limitation of structure identification.

This paper discusses the feasibility of unsupervised learning techniques to the classification of failure conditions. An example is presented in which the unsupervised fuzzy rulebase system successfully prognoses a new failure condition on which it was not previously trained.

Technical Approach

Data availability is one of the most critical factors for implementing a good diagnostic/prognostic system.

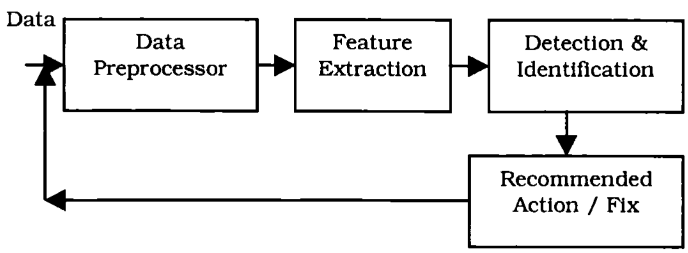

Figure 1: A Diagnostic System

A generic Diagnostic System construct is shown in Figure 1. The main components of such a system primarily consist of a Data Collection System, Data Preprocessing System, Feature Extraction System, Detection & Identification System, and finally to close the loop a recommended action, which could be an automated control action or a recommendation to perform a manual fix.

Once the data is collected from a system, the data usually needs to be preprocessed and extracted to a state where it can used for feature extraction. This step could include parity checking, data cleaning, to ensure data integrity. Feature extraction is implemented to extract relevant information by using either Statistical Analysis, Frequency Analysis, Wavelet Analysis, and/or any other feature extraction techniques which are helpful in discriminating and identifying one failure condition from another.

The Fault Detection and Identification module is where either a model-based technique or a soft-computing technique is used to implement a detection and/or identification scheme. Finally, the Recommended Fix / Action is an important module because it measures the reliability of the Diagnostic System. It is a performance metric from which the quality of the entire Diagnostic System is measured.

The Fault Detection and Identification module needs lot of data for training. A common shortcoming of this module is the fact that the accuracy and reliability of this module is entirely dependent on the training data set. If on-line learning capabilities are implemented in the system then the module can learn and adapt over time and the performance of the diagnostic module would continuously improve, which is desirable for many industrial applications. Accordingly an unsupervised learning design is implemented to detect new faults which the system is not trained to handle.

Unsupervised Learning

This diagnostic tool was developed as a standalone application in Java. This application is for a Image Quality test for a Magnetic Resonance machine. The users have the ability to train the system in the manual mode as well, by selecting the data sets that he wants to train the system, the data sets can be selected by pressing the CTRL key and clicking on the plot as shown in Figure 3. Once the plots are selected the diagnostic system uses only those data sets to train the system. In the automated mode a gross filter based the distance measure from the normal operating conditions is used as the benchmark for training the system.

After the features are extracted from the data set. Let us suppose the feature space is F= {f_1, f_2,..., f_n} where the feature could be a numerical or a logical value. It is assumed that the normal values or normal range of operation for this feature space are known. If the features are out of range then a fuzzy rule is formulated using those features.

The fuzzy rule may have only one-sided membership functions, i.e. the feature space might not have values above or below its normal operating region. A rule is formulated based on the features that have deviated from their normal operating region.

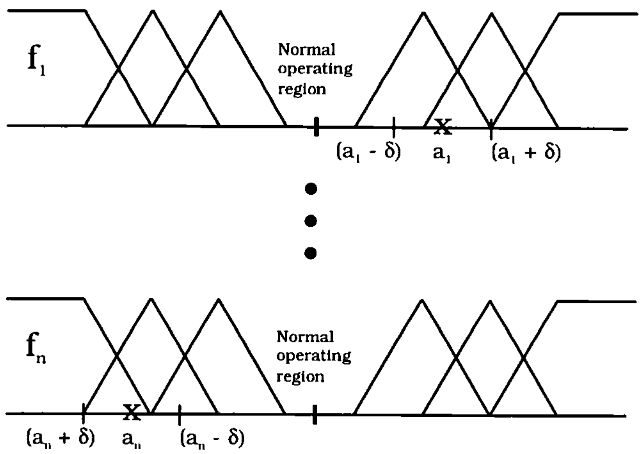

Figure 2: Fuzzified Feature Space

where,

a_n is the value of feature f_n for the current data set.
δ is the initialized operating envelope for fault classification.

A typical rule could be as follows:

IF f_1 is Positive High, AND ..., f_n is Negative High, THEN Fault Type is Fault A

Any new rule is first checked with existing rulebase and based on the rule that is fired, the current failure condition is classified as the fault type for that particular rule. A confidence metric is also assigned to the failure condition. If there are weak associations as a result of the classification process, new fault categories are assigned. If the value of δ is chosen to be small then there is a potential that the fault clusters in the feature space might explode, and if the value is too large then the misclassification rate might increase.

For initialization the value of δ is chosen to be a small, but as the system trains and learns, the value is increased as the confidence builds. This process might require manual training where the system is trained manually initially and then learn, as more data becomes available.

An Example

Magnetic Resonance (MR) machines run a System Performance Test (SPT) to analyze image quality. This data provides information about the image quality of the

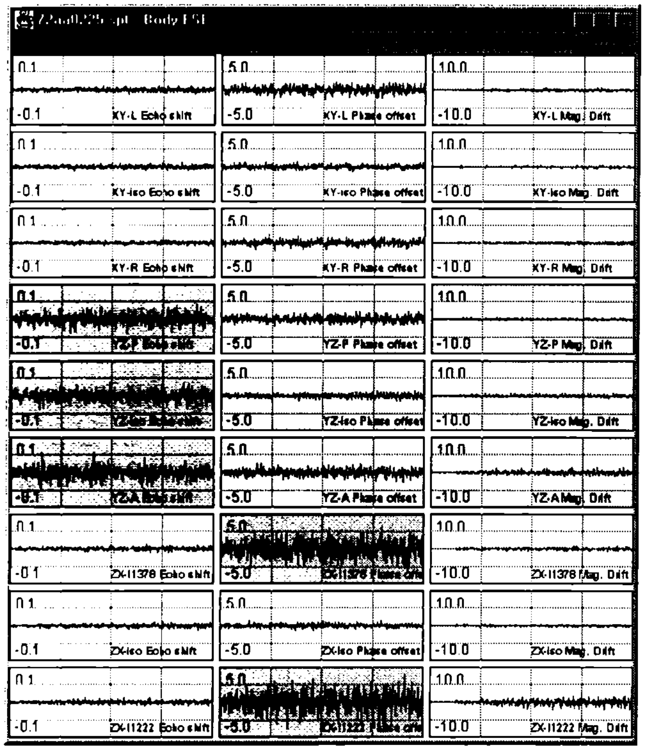

Figure 3: Manual selection of data sets for Training.

Scanner. Data sets are generated for various Readouts/Slice combinations. The effort is to analyze these data sets to assess the performance and quality of the MR machine.
The goal is to develop an intelligent system that will capture the most relevant and discriminating features of the SPT data, for each MR fault, and diagnose the data set and identify the fault category.

A confidence level is also assigned to each fault category, which is an indicator of the severity of the fault type and the confidence the diagnostic system has in its decision. Thus, detection and identification of faults from the signatures generated by the SPT data is the primary task of this algorithm.

The SPT data set can be divided into two categories, Fast Gradient Echo (FGRE) and Fast Spin Echo (FSE). This data is collected for both Head and Body phantoms. These tests are run at multiple locations, 3 locations for Body, and two locations for Head. There are three slices of data taken along X, Y and Z axis. Each data set consists of three variables, which are sampled over time to create three time series. The three variables are (a) Time Domain Echo Shift; (b) Constant Phase Shift; (c) Magnitude Drift. Thus, a complete data set consists of 90 data sets for a single SPT test. The FGRE data set consists of 256 sample points, while FSE data set consists of 512 sample points. A typical data structure is shown in Figure 4.

The data set is then diagnosed using the diagnostic system. If the system were already trained to diagnose the current failure condition then it would identify the failure condition and assign a confidence measure based on the degree of matching with the training data. If the system has not been trained for the current failure condition, it would assign a new Fault name to the condition and assign a low confidence value.

As an example a three dimensional feature space is shown in Figure 5. It shows how a system can be trained to diagnose different fault types. It is shown that it is possible that there is an overlap between two different fault types, in this case, Vibration and RF Transmit faults. The Diagnostic System assigns a higher degree of confidence to the RF Transmit Fault while assigning a lower degree of confidence to Vibration Fault Type.

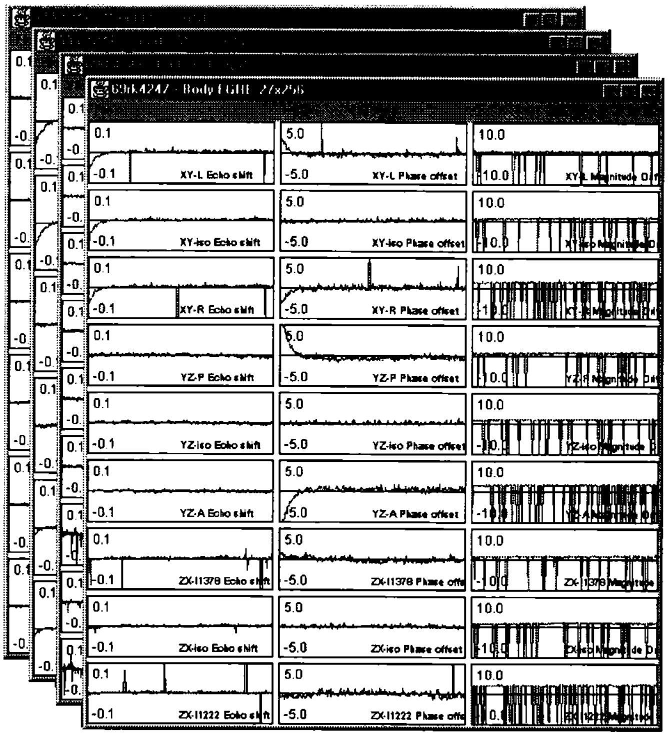

Figure 4: A Complete System Performance Test Data Set

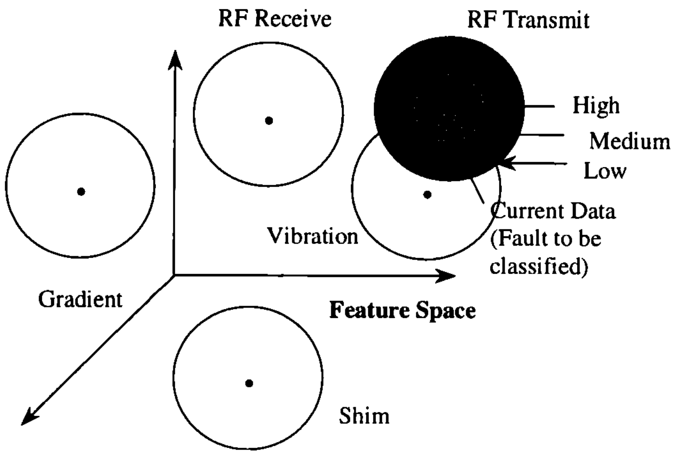

Figure 5: Feature space with various fault types

Conclusions

An automated fault diagnostic system has been developed. The proposed system has the capability to learn from data sets for new failure conditions. The system addresses an important aspect of diagnostic systems, which is maintainability. The system continuously learns as new data is made available and as new failure conditions arise. These algorithms have been developed, implemented and tested on data from Magnetic Resonance machines. The proposed architecture is easily extensible to other data intensive applications. This paper serves as a motivation for further research into optimal selection of the feature space, issues with conflict resolution and initialization of the diagnostic system. Future work needs to be done on handling multiple failure conditions. These issues need to be explored further to ensure a faster convergence of the fault clusters.

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