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Intelligent Vibration Signal Diagnostic System Using Artificial Neural Network

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Abstract—**In this paper artificial neural network (ANN) technologies and analytical models have been investigated and incorporated to increase the effectiveness and efficiency of machinery self diagnostic system. Several advanced vibration trending methods have been studied and used to quantify machine operating conditions. An on-line, multi-channel condition monitoring procedure has been developed and coded. The major technique used for self diagnostic is a modified ARTMAP neural network. The objective is to provide a rigid solution for condition-based intelligent self diagnostic system.**

Keywords-intelligent system; self diagnostic; artificial neural network; vibration signals diagnostic; fault diagnosis

I. INTRODUCTION

The subject of machine condition monitoring is charged with developing new technologies to diagnose the machinery problems. Different methods of fault identification have been developed and used effectively to detect the machine faults at an early stage using different machine quantities, such as current, voltage, speed, efficiency, temperature and vibrations. One of the principal tools for diagnosing rotating machinery problems has been the vibration analysis. Through the use of different signal processing techniques, it is possible to obtain vital diagnostic information from vibration profile before the equipment catastrophically fails. A problem with diagnostic techniques is that they require constant human interpretation of the results. The logical progression of the condition monitoring technologies is the automation of the diagnostic process. The research has been underway for a long time to automate the diagnostic process. Recently, artificial intelligent tools, such as expert systems, neural network and fuzzy logic, have been widely used with the monitoring system to support the detection and diagnostic tasks [1].

In this paper, an integrated Intelligent Self Diagnostic System (ISDS) based on real-time, multi-channel and neural network technologies is introduced. It involves intermittent or continuous collection of vibration data related to the operating condition of critical machine components, predicting its fault from a vibration symptom, and identifying the cause of the fault. ISDS contains two major parts: the condition monitoring system and the self diagnostic system. The fault diagnostic system is based on the ARTMAP fault diagnostic network developed by Knapp and Haung [2, 3, 4]. The ARTMAP network is an enhanced model of the ART2 neural network [5, 6].

II. CONDITION MONITORING SYSTEM

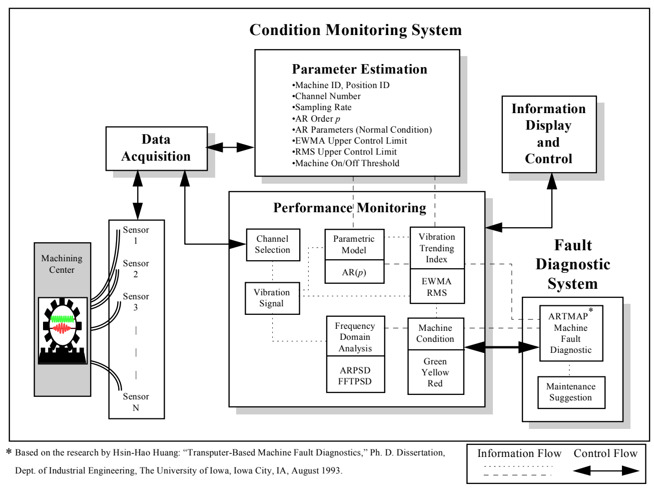

Figure 1. Overview of ISDS.

The condition monitoring system developed contains four modules: data acquisition, Parameters Estimation (PE), Performance Monitoring (PM), and Information Display and Control (IDC). The entire system was coded using C programming language. We have developed a user friendly graphic interface that allows for easy access and control in monitoring an operating machine. The system has been tested and verified on an experimental lab setting. The detailed procedure of ISDS and programming logic is discussed in the following sections.

A. Data Acquisition Module

The data acquisition module is more hardware related than the other modules. Vibration signals were acquired through accelerometers connected to a DASMUX-64 multiplexer board and a HSDAS-16 data acquisition board installed in a PC compatible computer. The multi-channel data acquisition program controlling the hardware equipment has been coded.

B. Programming Logic for Parameter Estimation (PE) Module

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The parameter estimation module is designed to estimate the parameters of the normal condition of a machine. It provides a procedure to set up the machine positions considered to be critical locations of the machine. The PE module must be executed before running the PM module. The information to be calculated in the PM module needs to be compared to the base-line information generated in the PE module.

The normal operating condition of a machine position is usually defined by experience or from empirical data. Generally speaking, a particular operation mode of a machine is selected and then defined as a "normal condition." However, this normal condition is not unchangeable. Any adjustment to the machine, such as overhaul or other minor repairs, would change its internal mechanisms. In this case, the normal condition must be redefined, and all the base-line data of the monitored positions on the machine need to be reset.

The PE procedure starts with specifying the ID of a machine, its location ID, and several other parameters related to each position, such as channel number and sampling rate. Then the upper control limits of the Exponentially Weighted Moving Average (EWMA) [7] and Root Mean Square (RMS) [8, 9] vibration trending indices are determined and an adequate Autoregressive (AR) order is computed. The AR time series modeling method is the most popular parametric spectral estimation method which translates a time signal into both frequency domain and parameter domain [10]. Once the AR order is determined, the AR parameters can be estimated through several normal condition signals collected from the particular position. A major issue with the parametric method is determining the AR order for a given signal. It is usually a trade-off between resolution and unnecessary peaks. Many criteria have been proposed as objective functions for selecting a "good" AR model order. Akaike has developed two criteria, the Final Prediction Error (FPE) [11] and Akaike Information Criterion (AIC) [12]. The criteria presented here may be simply used as guidelines for initial order selection, which are known to work well for true AR signals; but may not work well with real data, depending on how well such data set is modeled by an AR model. Therefore, both FPE and AIC have been adapted in this research for the AR order suggestion.

A setup file is then generated after the PE procedure is completed. This file, given a name that combines the machine ID and the position ID, consists of all the parameters associated with the specific position. The number of setup files created depends on the number of positions to be monitored in the PM mode, that is, each monitored position is accompanied by a setup file.

In order to perform a multi-channel monitoring scheme a setup log file is also generated. This file contains all the names of setup files created in the PE mode. Every time a new position is added its setup file name is appended to the setup log file. The setup log file is very important. It not only determines the channels needing to be scanned when the PM program is executed, it also provides the PM program with paths to locate all the necessary information contained in the setup files. In practice, after the PE procedure is completed, on-line performance monitoring of the machine (the PM mode) begins.

C. Programming Logic for Performance Monitoring (PM) Module

In the PM module, vibration data arrive through the data acquisition hardware and are processed by AR, EWMA, ARPSD, RMS, FFT spectrum, and hourly usage calculation subroutines. After each calculation the current result is displayed on the computer screen through the Information Display and Control (IDC) module.

IDC is in charge of functions such as current information displaying, monitoring control, and machine status reasoning. Details of these functions are given in the following section.

D. Information Display and Control (IDC) Module

Eight separate, small windows appear on the computer screen when the IDC module is activated. Each window is designed to show the current reading and information related to each calculation subroutine (e.g. AR, EWMA, ARPSD, RMS, and FFT spectrum) for the current position being monitored.

Window 1 is designed to plot the current time domain data collected from the data acquisition equipment. Window 2 displays both the AR parameter pattern of the current signal and the normal condition AR parameter pattern stored in the setup file generated in the PE module. Window 3 plots the current EWMA reading on a EWMA control chart and its upper control limit. Window 4 plots the current RMS value and its upper control limit on a RMS control chart. Both the RMS and EWMA upper control limits are calculated in the PE module. Window 5 displays the hourly usage and other information of the position. The hourly usage of the position is calculated based on the vibration level of that position. It is an estimated running time of the component up to the calculating point from the time this position is set up. Window 6 indicates the current performance status of the position. Three different levels of performance status: normal, abnormal, and stop, are designed. Each status is represented by a different color: a green light signals a normal condition; a yellow light represents an abnormal condition; and a red light indicates an emergency stop situation. The determination of the status of a position based on the current readings is discussed in the next section. Window 7 gives the current ARPSD spectrum, which is calculated based on the AR parameters from Window 2. Finally, Window 8 displays the current FFT spectrum by using the time domain data from Window 1.

In addition to real-time information display, the IDC module also provides a user-friendly graphic interface for monitoring control. A user can utilize the mouse to navigate around the computer screen and click on an icon to perform the specified function. For instance, to switch to another channel one can click on the "CH+" or "CH-" icon. Figure 2 shows the IDC screen layout developed.

E. Vibration Condition Status Reasoning

Based on the criteria stored in the setup file and the current readings, the EWMA and RMS control charts show whether the current readings are under or above their respective upper control limit. If both readings are under their corresponding control limits, then the position is in a normal condition. However, if either one of the control readings exceeds its upper control limit, the performance status reasoning program would turn on the yellow light to indicate the abnormality of the position. In this case, the fault diagnostic system is activated.

F. *Condition Monitoring Sample Session*

Data collection, in the form of vibration signals, was conducted using a test rig: a 1/2 hp DC motor connected to a shaft by a drive belt, two sleeve bearings mounted on each end of the shaft and secured to a steel plate, an amplifier to magnify signals, a DASMUX-64 multiplexer board, and a HSDAS-16 data acquisition board installed in a personal computer. Vibration signals were collected from the bearing using 328C04 PCB accelerometers mounted on the bearing housings. Using the test rig, the following sample session was conducted.

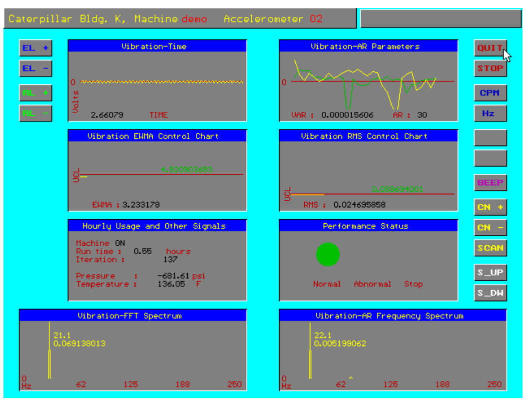

Figure 2. Condition Monitoring Information Display and Control (IDC) Screen Layout.

Assume that when the motor was turned on initially, it was running in normal condition. Later, a small piece of clay was attached to the rotational element of the test rig to generate an imbalance condition. This was used as an abnormal condition in the experiment. In the beginning, the setup procedure (PE) needed to be performed in order to obtain the base-line information. The sampling rate used was 1000 Hz and the sampling time was one second. The PE program first acquired eight samples and then took their average. Using the average normal signal, the AIC and FPE criteria were calculated. An AR order suggestion for the normal condition of the test rig was made. The AR order was fixed throughout the entire experiment. Once the AR order was known, the program started estimating the AR parameters and upper control limits of RMS and EWMA by collecting another eight data sets, calculating eight sets of AR parameters, and then averaging them. Finally, all parameters were stored in the setup file which would be used in the PM stage. An example of the normal condition parameters from a setup file are listed below:

- Machine ID: TESTRG
- Position ID: CHN1
- Channel number: 1
- Sampling rate: 1000
- AR order: 32
- AR parameters: ....
- EWMAUCL: 0.8912
- RMSUCL: 0.0367

When the machine was running in normal condition the readings of EWMA were approximately -0.486 far below the EWMAUCL of 0.8912. The readings of RMS were about 0.01895, and therefore, they were below the RMSUCL. As soon as an imbalance condition was generated the EWMA and RMS readings jumped to values of 3.3259 and 0.0504, respectively. The EWMA and RMS readings indicated the test rig was in an abnormal condition since both readings exceeded their respective control limits.

The machine condition monitoring mode switches to self diagnostic mode when at least one index exceeds its control limit. Once the system is in the diagnostic system, a detailed automatic analysis begins to identify the machine abnormality occurred. The next section explains the fault diagnostic system designed for this research.

III. ARTMAP-Based Self Diagnostic System

A. *Introduction to ARTMAP Neural Network*

The self diagnostic system in this paper employs a neural network architecture, called Adaptive Resonance Theory with Map Field (ARTMAP). The ARTMAP network is developed as an extension of the ART neural network series [6]. A modified ARTMAP architecture has been adopted in this paper in order to perform the supervised learning. The modified ARTMAP architecture is based on the research by Knapp and Huang [2, 4]. The major difference between the modified ARTMAP network and the ART2 network is the modified ARTMAP permits supervised learning while ART2 is an unsupervised neural network classifier.

B. *Performance Analysis of ARTMAP-Based Self Diagnostic System*

The performance of the ARTMAP-based self diagnostic system was validated by employing vibration signals from test bearings in the test rig. The two sleeve bearings were replaced by two ball bearings with steel housings. The new setup allows easy detachment of the ball bearing from the housing for exchanging different bearings.

Six bearings with different defect conditions were made. Table 1 describes these defective ball bearings. A two-stage vibration data collection was conducted for each bearing. Five sets of vibration signals were collected in the first batch, three sets in the second batch. A total of eight sets of vibration signals were collected under each defect. Therefore, there were a total of 48 data sets. All time domain vibration signals were transformed and parameterized through the ARPSD algorithm. The AR order used was 30. Thus, the dimension number for each AR parameter pattern was 31 (i.e., 30 AR parameters plus one variance). These 48

AR parameter patterns were used to train and test the ARTMAP-based self diagnostic system.

TABLE I. TEST BALL BEARINGS

Bearing Number	Defect Condition
1	Good bearing
2	White sand in bearing
3	Over-greased in raceway
4	One scratch in inner race
5	One scratch in one ball
6	No grease in raceway

TABLE II. BEARING TEST RESULTS OF ARTMAP-BASED ISDS

Pattern		**Bearing Number**											
Number		**1**		**2**		**3**		**4**		**5**		**6**	
Batch 1	**1**	Train		Train		Train		Train		Train		Train	
	2	1	3	2	6	3	1	4	2	5	6	6	2
	3	1	6	2	6	3	1	4	2	5	4	6	1
	4	1	6	2	6	3	1	4	2	5	4	6	2
	5	1	6	2	6	3	1	4	2	5	6	6	1
Batch 2	**1**	1	3	2	6	3	1	**5**	**4**	5	4	6	5
	2	1	3	2	6	3	1	**5**	**4**	5	4	6	5
	3	1	3	2	6	3	1	**5**	**4**	5	4	6	5

Note that the 512 frequency components in each ARPSD spectrum were compressed to only 31 parameters in each AR model indicating the system dealt with a significantly reduced amount of data; this is extremely beneficial in real-time applications.

The experimental procedure began with using the first pattern of all the conditions for training and then randomly testing the other seven patterns. In addition, the modified ARTMAP network was designed to provide two suggested fault patterns (i.e., the outputs of the first two activated nodes from the F_2 field). Table 2 summarizes the test results on diagnosing the 42 test patterns. The first column of Table 2 for each bearing type is the first identified fault from the network. It shows only 3 of the 42 test cases were mismatched in the first guess but they were then picked up correctly by the network in the second guess (see bold-face numbers in Table 2). Interestingly, these three mismatched patterns were from the second batch. If the profiles of Bearings 4 and 5 in the second batch were compared, then one could see the test patterns of Bearing 4 from the second batch were much closer to the training pattern of Bearing 5 than that of Bearing 4. This is why the network recognized the test patterns of Bearing 4 as Bearing 5 in its first guess. These test results clearly display the capability and reliability of the ARTMAP-based self diagnostic system and the robustness of using AR parameter patterns to represent vibration signals. For the efficiency of the ARTMAP training, the training time of one 31-point AR parameter pattern was less than one second on a PC.

IV. SUMMARY AND CONCLUSIONS

This paper presents an integrated Intelligent Self Diagnostic System (ISDS). Several unique features have been added to ISDS, including the advanced vibration trending techniques, the data reduction and features extraction through AR parametric model, the multi-channel and on-line capabilities, the user-friendly graphical display and control interface, and a unique machine self diagnostic scheme through the modified ARTMAP neural network.

Based on the ART2 architecture, a modified ARTMAP network is introduced. The modified ARTMAP network is capable of supervised learning. In order to test the performance and robustness of the modified ARTMAP network in ISDS, an extensive bearing fault experiment has been conducted. The experimental results show ISDS is able to detect and identify several machine faults correctly (e.g., ball bearing defects in our case).

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