Intelligent Data Reduction Algorithm for Sensor Network based Fault Diagnostic System

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Abstract

In the modern life, machines are used for various areas in industries as the advance of science and industrial development has proceeded. In many machines, the rotating machines play an important role in many processes. Therefore, the development of fault diagnosis and monitoring system for rotating machines is required. An ubiquitous sensor network (USN) is a combination of the key computer science and engineering area technology including the wireless network, embedded system hardware and software, communication, real-time system, etc. It collects environmental information to realize a variety of functions. In this work, a data reduction algorithm for USN based remote fault diagnostic system which can be easily applied to previously built factories is proposed. To verify the feasibility of the proposed scheme, some simulations and experiments are executed.

Key Words : rotating machine, Ubiquitous Sensor Network, fault diagnostic system

1. Introduction

In the modern life, machines are used for various areas in industries as the advance of science and industrial development has proceeded. The importance of machines is undeniable, the more we use the machines the more safety is required. In many machines, the rotating machines play an important role in many processes. Therefore, the development of fault diagnosis and monitoring system for rotating machines is required to provide efficient methods for early possible detection when a machine is starting to get faulty. Until recently, the fault diagnosis of rotating machines relies on the acoustic sense or vision of the experts. But the development of sensor technologies and the stored information on the faulty machines made the diagnostic system more reliable. Nowadays, fault diagnosis approaches for rotating machines have focused on the development of signal processing techniques on the measurements, such as vibration and temperature. However, information from a single measurement may not give a reliable result, due to the complicated dynamic characteristics of the rotating machines and the sensor noise. To circumvent this problem, a multi-sensor approach has been presented [1-2].

An ubiquitous sensor network (USN) is a combination of the key computer science and engineering area technology including the wireless network, embedded system hardware and software, communication, real-time system, etc [3]. It collects environmental information to realize a variety of functions, through a countless number of compact wireless nodes that are located everywhere to form an ad hoc arrangement, which does not require a communication infrastructure. USN is not simply a network but can be an intelligent information infrastructure used to support a multitude of different applications.

Generally, newly built factories tend to be equipped with SCADA for the better maintenance and optimal operation. However, there are many factories that are not equipped with SCADA. In this case, reinstalling the SCADA system requires lots of money and incurs the shutdown of factories. Therefore, some new schemes are required for this. In this work, USN based remote wireless fault diagnostic system which can be easily applied to previously built factories without SCADA is proposed to improve the performance of the system.

2. Background and problem statement

2.1 Fault detection in rotating machines by vibration signal

Machines with moving parts give rise to vibrations and consequently noise. The setting up and the status of each machine yield to a peculiar vibration signature. Therefore, a change in the vibration signature, due to a change in the machine state, can be used to detect incipient defects before they become critical. This is the goal of condition monitoring, in which the number of signal processing techniques that can be used in order to extract interesting information from a measured vibration signal. Several researches seek to detect rotating machine defects using a range of techniques including synchronous time averaging, Hilbert transformation-based demodulation, continuous wavelet transform and spectral correlation density function [4-5].

Although there are a large number of signal processing techniques that can be used in order to extract interesting
information from a measured vibration signal, frequency domain based scheme is utilized in this work. Generally, potential defects can be analyzed by the frequency domain spectrum of the vibration signal. In order to calculate the frequency spectrum of a sampled time signal, the Fast Fourier Transform algorithm can be used as a numerically efficient method [6]. It is important to notice that all digital Fourier transform assumes stationary signals. Illustrative examples for vibration signals and its FFTs are shown in fig. 1. As can be seen in fig.1, fault detection can be effectively carried out by just comparing the power spectral density with its normal values.

![FFT of angle misalignment and structure looseness](image)

Fig. 1 Time signal and its FFT in case of (a) angle misalignment and (b) structural looseness of rotating machine

2.2 Ubiquitous Sensor Network

An ubiquitous sensor network (USN) is a combination of the key computer science and engineering area technology including the wireless network, embedded system hardware and software, communication, real-time system, etc. It collects environmental information to realize a variety of functions, through a countless number of compact wireless nodes that are located everywhere to form an ad hoc arrangement, which does not require a communication infrastructure. USN is not simply a network but can be an intelligent information infrastructure used to support a multitude of different applications.

USN can deliver information to “anywhere, anytime, by anyone”, it consists of sink node and sensor nodes. Every tiny node is connected to other (one or more) by managing of a sink node to form a sensor network. We developed USN with IEEE 802.15.4 which is called ZigBee standard [7].

![An illustration of USN](image)

Fig. 2 An illustration of USN

2.3 Efficient data transmission scheme for fault detection

In view of data transmission in sensor network, four delivery models are used: continuous, event-driven, observer initiated and hybrid. In the continuous model, sensor uses a predetermined rate by which to transmit their data continually. For example, a sensor may be required to transmit a temperature reading every five minutes. In the event-driven model, sensors will only transmit data if an event of interest takes place. In the observer-initiated model, sensors will only transmit data when the observer issues a request. In the hybrid model, the first three models coexist in the same network.

As explained in section 2.1, spectrum data for the current status of rotating machine should be continuously transmitted to sink node for real-time fault detection. However, if there are many sensor nodes installed on rotating machines in USN field, data collision caused by every nodes trying to send its spectrum data may takes place. Furthermore, there may be the cases where data changes slowly or even do not change in a long period of time. Therefore, development of an efficient data transmission algorithm is required for remote wireless fault detection system for rotating machine. In this work, in order to solve the aforementioned problems, DPCM (Differential Pulse Coded Modulation) algorithm which has been effectively applied in CAN network [8] is introduced.

3. The proposed USN-based remote fault diagnostic system for rotating machine identification

In this work, wireless remote fault diagnostic system based on USN is proposed with the goal of continuous monitoring in mind. The proposed system is shown in fig.3.

The proposed system consists of many sensor nodes which are installed on rotating machines and a sink node which is connected with server PC. Each sensor node samples vibration signal from the machine periodically and the sampled data are further transformed by FFT algorithm. Spectral data
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representing the current status of rotating machine should be transmitted to remote server PC by using similar DPCM algorithm.

With the received spectral data in server PC, fault detection and diagnosis are performed. If some faults are detected, server PC will send out emergency messages to the system operators. The detailed descriptions are given in the following.

3.1 Sensor node for wireless fault diagnosis

The internal structure of a sensor node is shown in fig. 4. Each sensor node is composed of three components, such as DSP, RF communication module and power module. DSP module plays an important role in this work. It is primarily used for sampling vibration signal and performing FFT continuously. After finishing FFT, it also decides when/what to send to remote sink node. Finally, spectral data which are determined to be sent to remote sink node are transmitted to remote server via RF communication module. Spectral data from each sensor nodes are gathered in remote server PC. By using these data, a certain fault diagnostic algorithm is executed.

In this work, TinyOS is used as an operating system for RF communication module. TinyOS is an operating system designed specifically for sensor networks. Combined with a family of wireless sensor devices, TinyOS is currently used as a research platform by several institutions.

3.2 Efficient feature data transmission algorithm

Each sensor node periodically calculates FFT to get spectral data for the vibration signal from the rotating machine. Its spectral data should be transmitted to a remote sink node every fixed time. However, if there are many sensor nodes which try to send its spectral data to a sink node simultaneously, data traffic and communication delays may be caused. This may lead to the degradation in fault diagnosis system and may put the machine’s life in danger. In order to overcome these problems, a suitable data reduction technology should be required. In this work, a new data reduction and transmission algorithm is proposed: only when the content of spectral data is obviously changed, the packet should be transmitted to a remote sink node. The entire data compression process is depicted using the flow chart of fig.5.

Each sensor node keeps a copy of the most recently transmitted message in the TX_BUF. Likewise, a remote sink node has a corresponding buffer called RX_BUF which keeps a copy of most recently received message. Assume that each sensor node transmits a message every time units. When the sensor node transmits a message after time units, the sensor node compares the data field of the previously saved message in the TX_BUF, with the current message being transmitted. If none of the bytes in the spectral data changes in their value, the entire new message is not transmitted. A remote sink node in the network assumes the most recent value of the message as the current value of the message.

![Fig. 3 Wireless remote fault diagnostic system based on USN](image1)

![Fig. 4 Structure of sensor node for wireless fault detection system](image2)

![Fig. 5 The flow chart of the proposed data transmission algorithm](image3)
3.3 Detailed description of proposed data transmission algorithm

As described in previous section, TinyOS was ported on our sensor node. In TinyOS, the actually transmitted packet is an Active Message and the data frame structure of the message is shown in fig.6. TOSmsg can be transmitted to a specific node (addressed with a 16bit ID) or to a broadcast address (0xffff). TinyOS provides a namespace for up to 256 types of messages, each of which can be associated with a different software handler. Message types allow multiple network or data protocols to operate concurrently without conflict. TOSmsg also provides the abstraction of an 8-bit message group; this allows logically separate sensor networks to be physically co-present but mutually invisible, even if they run the same application.

As can be seen in fig.6, actually transmitted spectral data should be placed in the data field. There are two types of data messages in the proposed data transmission algorithm;
- Normal Message
- DPCM Message

For the discrimination of these messages, Type field in the TOSmsg is used. In our application, unused identifier is used.

Normal message should be transmitted only one time at the beginning of the transmission process. In normal message, spectral information (spectral magnitude according to the spectrum band) are included. Generally, it is not easy to transmit the whole spectral data with only one data packet. Therefore, for the transmission of normal spectral data, sequential data packets are made and should be transmitted according to their sequence number. The detailed explanation on normal Message is described in table 1.

In this work, adaptive data reduction algorithm which is called delta modulation or differential pulse coded modulation (DPCM) is utilized for the efficient data transmission. It is based on the principle that instead of sending the absolute value of the spectral data at each time, only the changes in the magnitude of the spectral data from one time instance to another are transmitted. If one or more spectral data at the time of m+1 change in their value compared with that at the time of m, sensor node executes the following series of steps.

1. Sensor node computes a delta compression code (DCC). A value of “1” in the DCC indicates the delta change in the value of the spectral data. A value of “0” in DCC indicates no change in the spectral data.
2. Since a copy of the message transmitted at time m is stored in TX_BUF, the sensor node computes differences (deltas) in the value of the corresponding spectral data at time m with at the time of m+1.
3. The delta compressed spectral data is transmitted to the remote sink node.

Fig.7 and fig.8 show the format of the normal message and DPCM message respectively.

By introducing DPCM algorithm, data packets which should
be transmitted can be considerably reduced.

Table 1. Explanation on each field of Normal Message

<table>
<thead>
<tr>
<th>Field</th>
<th>function</th>
</tr>
</thead>
<tbody>
<tr>
<td>Source</td>
<td>Address of sensor node which transmits the current data packet</td>
</tr>
<tr>
<td>PGN</td>
<td>Packet group number which indicates current packet belongs to the same group</td>
</tr>
<tr>
<td>Data</td>
<td>Spectral Data</td>
</tr>
<tr>
<td>APN</td>
<td>Number of packets which should be transmitted in case of multiple packets</td>
</tr>
<tr>
<td>CPN</td>
<td>Ordinal number of the current packet which indicates the current packet</td>
</tr>
</tbody>
</table>

Table 2. Explanation on each field of DPCM Message

<table>
<thead>
<tr>
<th>Field</th>
<th>function</th>
</tr>
</thead>
<tbody>
<tr>
<td>Source</td>
<td>Address of sensor node which transmits the data packet</td>
</tr>
<tr>
<td>PGN</td>
<td>Packet group number which indicates current packet belongs to the same group</td>
</tr>
<tr>
<td>Res</td>
<td>Reserved area</td>
</tr>
<tr>
<td>DCC</td>
<td>Delta compression code</td>
</tr>
<tr>
<td>Data</td>
<td>Changed Spectral Data</td>
</tr>
<tr>
<td>APN</td>
<td>Number of packets which should be transmitted in case of multiple packets</td>
</tr>
<tr>
<td>CPN</td>
<td>Ordinal number of the current packet which indicates the current packet</td>
</tr>
</tbody>
</table>

3.4 Data Decompression process

The remote sink node decompresses the delta-compressed message received from the remote sensor nodes. The following steps are executed to perform data-decompression. Assuming that a delta-compressed message Dci is received.

**Step 1:** The sink node checks the type field of the Dci message. If the message is a delta-compressed message, the first byte in the data field of the message is treated as the DCC.

**Step 2:** The receiving node fetches a copy of the most recently received ci from the RX_BUF.

**Step 3:** The DCC acts as an index to the corresponding spectral fields within the delta-compressed message. For example, a value of “1” in the first bit position of the DCC means that the first field within the message is a delta of the first field within the message ci from RX_BUF. This delta value is either added to or subtracted from the corresponding field within the message ci from RX_BUF to get the new value.

**Step 4:** A value of “0” in the DCC means that the corresponding data have not changed its value since the previous transmission.

**Step 5:** The receiver reconstructs all the spectral data within the message in a similar fashion.

**Step 6:** The receiver then updates the RX_BUF with this new value, overwriting the previous ci.

3.5 Fault Diagnostic algorithm

By using the data reduction algorithm described in the previous section, remote sink node can get hold of corresponding spectral data from each sensor node. With the received spectral data, fault diagnosis can be effectively carried out. Generally, there is a corresponding fundamental frequency in each fault. If a fault occurs in a rotating machine, the spectrum amplitude of the corresponding frequency changes.

![Fig. 9 Structure of back-propagation neural network](image)

In this work, back-propagation neural network shown in fig.9 is utilized for fault diagnosis.

The structure of BP includes three layers, input layer, hidden layer and output layer. The variable “M” means the total neuron number in input layer, the variable “N” means the total neuron number in hidden layer, and the “L” means the total neuron number in output layer. There are weight values $W_{NM}$ between the input and the hidden layer. And there are weight values $W_{LN}$ between the hidden and the output layer. The operation of BP is divided into three parts.

1. Feed-forward stage:

   $$v_j = W_{LN}(n) \cdot u_{j+1}(n)$$ \hspace{1cm} (1)

   $$O_j(n) = \phi(v_j(n)) = \frac{1}{1 + \exp(-v_j(n))}$$ \hspace{1cm} (2)

   where $u_j(n)$ means the input, $u_{j+1}(n)$ means the output of hidden layer, and $O_j(n)$ is the output. In addition, the sign $\phi$ represents the activation function.

2. Back-propagation stage:

   $$\delta_j(n) = e_j(n) \cdot \phi'(v_j(n))$$

   $$= (d_j(n) - O_j(n))O_j(n)(1 - O_j(n))$$ \hspace{1cm} (3)

   where $\delta_j(n)$ is the local gradient function, $e_j(n)$ is the error function, $O_j(n)$ represents the actual output and $d_j(n)$ means the desired output.
(3) Adjust weight value:
\[ W_{NM}(n+1) = W_{NM}(n) + \Delta W_{NM}(n) \]
\[ = W_{NM}(n) + \eta \delta_j(n) \cdot y_j(n) \]  
(4)

where \( \eta \) represents the learning rate and the available value is situated between 0.1 to 1. \( \delta_j(n) \) represents the calculation result of step2.

With BP neural network, both the received spectral data from each sensor node and its corresponding output are utilized for training BP neural network.

4. Simulation

The purpose of this part is to show the performance of the proposed system.

4.1 Simulation study

This section presents a performance analysis of the proposed data-reduction algorithm. The performance of the algorithm has been measured in terms of average message transmission delay. For the simulation, a special program has been coded in C# to simulate the proposed data-reduction algorithm. For the purpose of comparison, the same simulation program has been executed with and without data-compression algorithms. The following assumptions are made.

First, there are many sensor nodes and one sink node in USN field. Second, distance between every sensor nodes and sink node is within a single-hop distance. This means that star-typed network topology is assumed.

![Fig. 10 Total message transmission time according as the number of sensor nodes varies](image)

To test the performance of the proposed scheme, total transmission time which is required for all the sensor nodes to transmit their spectral data to a remote sink node is investigated according as the number of sensor nodes varies. Each sensor node has its spectral data which are randomly generated. Therefore, it depends on the status of spectral data whether data-reduction algorithm is applied or not. The simulation result is shown in fig.10. As can be seen in fig.10, as the number of sensor nodes increase, total transmission time increases in both cases. However, the performance in the case of DPCM is better than that of normal transmission method. Thus it is believed that the results shown in this work indicate a very realistic performance of the proposed data-reduction algorithm.

4.2 Experimental result

The complete experimental arrangement of the proposed system is shown in fig.11. The system is composed of three-phase induction motor, accelerometer, digital signal processor, Zibgee sensor node and remote sink node. Three-phase induction motor has the output power of 0.75KW and accelerometer is installed on motor housing to measure the vibration. Output of the accelerometer is processed by DSP(TMS 320F2812) which has 12 bit A/D converter inside and calculates the spectral data by using FFT algorithm. In this experiment, sampling frequency is chosen to be 1KHz and 128 point FFT is executed every one minute. Therefore, a total of 64 spectrum data are obtained and these should be transmitted in normal mode or DPCM mode according to its status. Furthermore, DPCM algorithm is executed inside of DSP and its result is transmitted to Zigbee sensor node via RS232 interface. Finally, Zigbee sensor node transmit DCPM or normal data to remote sink node(server computer). In server computer, received spectral data transmitted from remote sensor nodes are gathered and fault diagnostic algorithm is executed by using reconstructed spectral data.

![Fig. 11 Configuration of the vibration monitoring system](image)

In this work, three types of faults are considered to verify the performance of the fault diagnostic scheme. These faults include the rotating machine with a structural looseness, with a bearing housing fault and with an unbalanced load. The corresponding vibration signals to each faults are shown in fig. 12.
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13, the magnitude of FFT corresponding to each faults is different to each other. Therefore, some dominant frequency bands shown in table 3 are utilized as a feature vector for training.

Table 3. Frequency range used for feature vector

<table>
<thead>
<tr>
<th>Feature vector</th>
<th>Frequency range (Hz)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>25 – 38</td>
</tr>
<tr>
<td>2</td>
<td>54 – 67</td>
</tr>
<tr>
<td>3</td>
<td>85 – 94</td>
</tr>
<tr>
<td>4</td>
<td>113 – 125</td>
</tr>
<tr>
<td>5</td>
<td>144 – 155</td>
</tr>
<tr>
<td>6</td>
<td>175 – 181</td>
</tr>
<tr>
<td>7</td>
<td>207 – 210</td>
</tr>
</tbody>
</table>

The number of neurons in each layer of BP neural network is 7, 40 and 2 respectively. The trained BP neural network was investigated with unused feature data and its diagnostic result is shown in table 4.

Table 4. Diagnostic result

<table>
<thead>
<tr>
<th>Kind of Fault</th>
<th>rate(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>normal</td>
<td>100</td>
</tr>
<tr>
<td>looseness fault</td>
<td>87</td>
</tr>
<tr>
<td>bearing housing fault</td>
<td>81</td>
</tr>
<tr>
<td>load fault</td>
<td>93</td>
</tr>
</tbody>
</table>

As can be seen in table 2, the diagnostic result is desirable.

5. Conclusion

In the work, an efficient data transmission algorithm which can be utilized in USN based fault detection system for rotating machines has been proposed. To verify the performance of the proposed system, some simulation studies and experiments are carried out. From the simulation studies, we know that using DPCM algorithm is very efficient for transmitting spectral data for real time monitoring and fault diagnosis.

References


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