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Fault diagnosis of rotating machine by thermography method on support vector machine †

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Abstract

Feature-based classification techniques consist of data acquisition, preprocessing, feature representation, feature calculation, feature selection, and classifiers. They are useful for online, real-time condition monitoring and fault diagnosis / features, which are now available with the development of information technologies and various measurement techniques. In this paper, an intelligent feature-based fault diagnosis is suggested, developed, and compared with vibration signals and thermal images. Fault diagnosis is performed using thermal imaging along with support vector machine (SVM) classification to simulate machinery faults, resulting in an accuracy level comparable to vibration signals. The observed results show that fault diagnosis using thermal images for rotating machines can be applied to industrial areas as a novel intelligent fault diagnostic method with plausible accuracy. It can be also proposed as a unique non-contact method to analyze rotating systems in mass production lines within a short time.

Keywords: Condition monitoring; Fault diagnosis; Rotating machine; Support vector machine (SVM); Thermal image

1. Introduction

Condition monitoring and fault diagnosis of operating machines has received considerable attentions because of its potential advantages, such as reduced maintenance cost, improved productivity, and increased machine operation [1]. Williams et al. [2] adopted the British standard (BS 3811:1984) and defined condition monitoring as the continuous or periodic measurement and interpretation of data to indicate the condition of an item and determine its need for maintenance. Condition monitoring is needed to guarantee the survival of a machine so that incipient fault can be detected and diagnosed as early as possible. The possibility of failure cannot be avoided in machines, but the early diagnosis of incipient failure is useful to avoid machine breakdowns. When fault occurrence exists in the machines, symptoms will be present, such as excessive vibration and noise, extremely high temperature, and oil debris. Vibration analysis, thermography, motor current signature analysis, airborne ultrasound analysis, and other technologies can be used as condition monitoring and fault diagnostic techniques.

Predictive maintenance evaluates the condition of equipment through periodic or continuous monitoring. The ultimate goal of predictive maintenance is to perform maintenance at a scheduled point in time when the maintenance activity is cost effective and before the equipment loses performance within a threshold.

Vibration sensors have been used extensively as fundamental tools for machine condition monitoring for approximately four decades [3]. The sensors are used for their effectiveness in measurement process and data analysis by representing machine conditions. Vibration signal monitoring in rotating machines remains effective for obtaining machine behavior. It can extract machine conditions through signal analysis in time and frequency domains. Many researchers have reported on machine fault diagnostic techniques that use vibration sensors with the application of an intelligent system in their proposed methods [4-7]. The use of temperature monitoring for journal bearings has also been reported [8-10]. However, these works do not employ any intelligent systems for monitoring and diagnosis. Temperature monitoring using a thermocouple sensor is usually employed as a secondary sensor instead of vibration and AE sensors. Therefore, reports that employ intelligent diagnostics using such sensors are rarely found.

Another method that has recently become popular in machine condition monitoring and fault diagnosis is thermography. Good performance and simplicity have made this tech-

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nique highly popular in engineering maintenance. Thermography has been used in a wide range of areas, such as mechanical, electrical, petrochemical, material, medical, structural, and architecture. The use of thermography in machine condition monitoring and diagnosis has been reported; infrared thermography (IRT) was performed to detect faults in rolling elements that bear degradation [11]. Evaluation of thermal data image for machine diagnosis was also reported [13]. Principal component and independent component analyses extract image features. Their proposed system was augmented using support vector machine (SVM) for the diagnostic process. A recent publication implemented feature extraction of images through two-dimensional (2-D) discrete wavelet transform [14]. The intelligent system used the SVM for machine diagnosis.

However, the lack of trained experts has been a serious issue in industries for several decades. The effort to solve this problem depends on the expert system or on machine learning systems. Some studies have investigated fault diagnosis that uses artificial intelligence with vibration signal as the alternative. However, few studies have investigated the intelligent fault diagnosis of rotating machines with thermal images, even though thermography is a successful diagnostic tool for machines. Hence, the motivation of this research is to establish an intelligent fault diagnostic method that can be effectively applied in machine-based thermal images and vibration. SVM, a relatively new computational learning method based on statistical learning theory, was introduced by Vapnik et al. [15, 16] to serve as ES and to carry out intelligent machine condition monitoring system. SVM became famous and popular in the machine learning community due to its excellent generalization ability, which is better than that of traditional methods such as neural network. Therefore, SVM has been successfully applied in a number of applications, ranging from face detection, verification, and recognition; object detection and recognition; as well as handwritten character and digit recognition; to text detection and categorization; speech and speaker verification, recognition, information; and image retrieval, prediction.

Recently, significant technological developments have been made in the field of IRT, resulting in the appearance of low-cost IRT instruments. These developments have not only popularized the monitoring technology, but have also caused a dramatic increase in the number and variety of IRT applications. To use the thermography correctly and extract more useful information from thermal images, users must know its exact advantages and limitations. A predictive maintenance using IRT is widely applied in the industrial field for high- and low-voltage electric equipment, rotating machinery, and other potential applications because heat is often an early symptom of equipment damage or malfunction.

This paper focuses on developing a novel method that uses the SVM algorithm for fault diagnosis through IRT, which can be an alternative to vibration signal analysis. The aim of this research is to redevelop and modify the SVM algorithm and to combine it with other preprocessing methods to obtain better performance from the classification function of SVM.

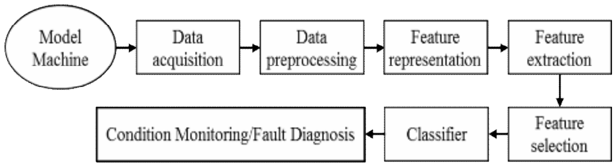


Fig. 1. Feature-based condition monitoring and fault diagnostic system [1].

2. Feature-based diagnostic techniques

2.1 Feature extraction and selection

Too many features can cause cures of dimensionality, whereas too few features may greatly degrade classification accuracy. Two methods can effectively reduce feature dimensionality: feature extraction and feature selection. Methods that create new features based on transformations or combinations of the original feature set are called feature extraction. Feature selection refers to algorithms that select the best feature subset from all the features. The feature extraction often precedes feature selection. It also leads to savings in computation time, shown in Fig. 1. Feature selection contributes to monitoring and diagnosis accuracy. SVM is a relatively new computational learning method based on statistical learning theory. Introduced by Vapnik et al., SVM has become famous and popular in the machine learning community due to its excellent generalization ability compared with that of traditional methods such as neural network [16].

2.2 Binary classification using SVM

In the machine condition monitoring and the fault diagnosis, the SVM is employed to recognize certain special patterns from the acquired signal. These patterns are then classified according to the fault occurrence in the machine. After the signal acquisition, a feature representation method can be performed to define the features, such as the statistical feature of the signal, for classification purposes. These features can be considered the patterns that should be recognized using SVM.

For linear data, determining the hyperplane $f(\mathbf{x}) = 0$ that separates the given data is possible.

$$f(\mathbf{x}) = \mathbf{w}^T\mathbf{x} + b = \sum_{j=1}^{M} w_j x_j + b = 0 \qquad (1)$$

where $\mathbf{w}$ is the M-dimensional vector and b is a scalar. The complete equation can be written as

$$y_i f(\mathbf{x}_i) = y_i(\mathbf{w}^T\mathbf{x}_i + b) \geq 1 \quad \text{for} \quad i = 1, 2, ..., M \qquad (2)$$

where the hyperplane is the classifier of input data in either the positive class or the negative class. Vector $\mathbf{w}$ and scalar b are used to define the position of the separating hyperplane. The decision function is made using sign $f(\mathbf{x})$ to create a separating hyperplane that classifies input data in either a positive class or a negative class. A distinctly separating hyperplane should satisfy the constraints indicated below.

$$\begin{aligned} f(\mathbf{x}_i) &= 1 \quad y_i = 1 \\ f(\mathbf{x}_i) &= -1 \quad y_i = -1 . \end{aligned} \tag{3}$$

For the nonlinear function, the equation below can be used to solve the dual optimization problem.

$$f(\mathbf{x}) = sign\left(\sum_{i,j=1}^{M} \alpha_i y_i (\mathbf{x}_i \mathbf{x}_j) + b\right) \tag{4}$$

where α_i is the coefficient required to express the w and solve the minimum of **w.**

For the multi-class classification, different approaches, such as one-against-one (OAO) and one-against-all (OAA), can be used in the fault diagnosis of machine systems. A detailed discussion on these approaches can be found in Ref. [17].

3. Experimental details

The experiment was carried out using a small machinery fault simulator (MFS) that can simulate the fault modes that commonly occur in rotating machinery, such as misalignment, unbalance, ball bearing faults, and other mechanical fault situations. The machine has a range of operating speeds up to 6000 rpm. The fault simulator has a 0.5 kW motor, 60 Hz, three-phase induction motor, a coupling, bearings, discs, and a shaft. The faulty conditions to be analyzed are bearing fault, unbalance, misalignment, and looseness. A normal condition (healthy, condition 1) is a benchmark for comparing the four faulty conditions. The MFS was operated at 1800 rpm. The faulty conditions are described with normal, unbalanced, looseness, misalignment and bearing fault cases.

When tested for each faulty condition, the machine should be operated for over 20 minutes for each fault to ensure the temperature saturation of the bearings and motors. The objective of this experiment is to figure out the IR characteristics of the diagnosis for faulty motors. This information is used to process a variety of features to obtain the difference between faulty motors and to confirm a possibility as a mechanical fault diagnostic tool.

The vibration and thermography signature for detecting and diagnosing faults in an induction motor may be considered as a kind of pattern recognition paradigm. It consists of data acquisition; signal processing; feature extraction, selection, and reduction; and fault diagnosis. The aim of this method is to find a new alternative source feature and a machine diagnostic technique using SVM. A novel fault diagnostic method for induction motors is proposed based on feature extraction, distance evaluation technique, and SVM multi-class classification. For one-dimensional signals, the acquisition of vibration data was carried out and then followed by feature calculation. The statistical features were calculated from the time and frequency domains of the vibration signals. Feature extraction using a nonlinear technique via component analysis reduces dimensionality. This step is performed to remove redundant features and even degrade the performance of the classifier. Feature selection was performed using the distance of evaluation technique. This method was chosen due to its simplicity and reliability. Finally, the classification process for diagnosing faults was carried out using SVM based on multi-class classification. For 2-D signals, thermal images were acquired simultaneously with vibration data. Then, the format of thermal images was changed from RGB to CIELab space for feature calculation. The transformed images were more useful because they were of a color scale independent of the device. Next, the color differences were grouped according to k-means algorithms to segment the region of interest and reduce data. The SVM algorithm was used to calculate shape features, which could represent the thermal pattern from images calculated and classify the diagnosis of faults. The vibration signals were acquired using a dynamic analyzer (LMS, PIMENTO) with eight channels, 24bit A/D converter, through four accelerometers with a sensitivity of 100 mV/g on the vertical and horizontal directions. The sampling rate was 5 kHz, and data were recorded every 20 sec per fault. The thermal images of the simulator were recorded using a cooled-type IR camera (FLIR, SC 5000). The acquired images were stored in a notebook computer in RGB format, with an image size of 320 × 256 pixels and 60 Hz frame rate. Fig. 2 shows the small MFS.

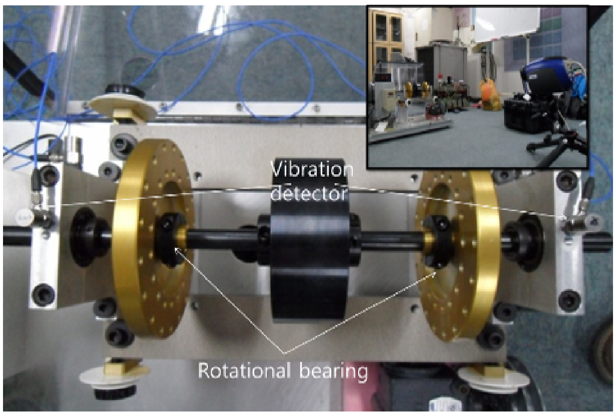


Fig. 2. Experimental setup for vibration detection of the bearing house using a small MFS. Insert shows the thermography measurement system of MFS.

To digitize and present radiated energy as a form of color gradient in thermal images, the measured thermal images were reformed as a matrix for the computational process and transformed into CIELab color space coordinates. CIELab cannot be transformed directly from RGB, and should first be transformed into CIEXYZ. The CIEXYZ system can be calculated using the standardized transform as follows [18]:

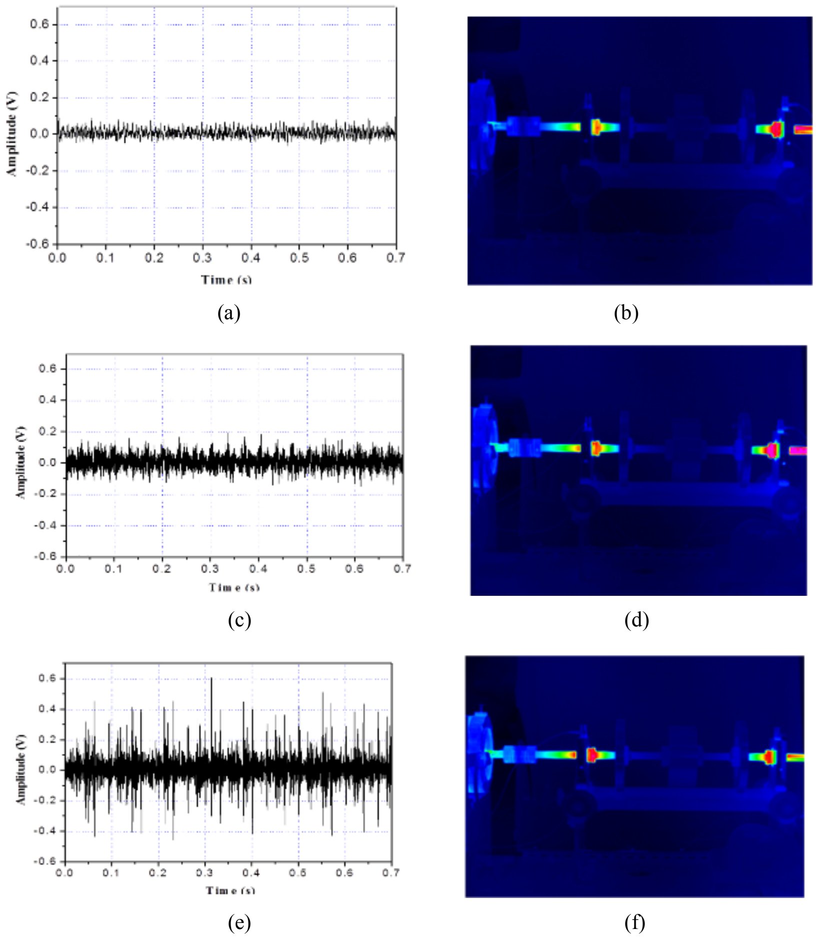


Fig. 3. Time signal and thermal images of MFS operating under (a-b) normal; (c-d) parallel misalignment; (e-f) bearing outer race fault conditions.

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \frac{1}{0.17697}\begin{bmatrix} 0.49 & 0.31 & 0.20 \\ 0.17697 & 0.81240 & 0.01063 \\ 0.00 & 0.01 & 0.99 \end{bmatrix}\begin{bmatrix} R \\ G \\ B \end{bmatrix}.$$

The CIELab can be calculated with these X, Y, Z values, and X_n, Y_n, Z_n, CIE tristimulus values of the reference white point. Thus, L^*, a^*, b^* are given as follows [19]:

$$\begin{aligned} L^* &= 116 \cdot f(Y/Y_n) - 16 \\ a^* &= 500\left[f(X/X_n) - f(Y/Y_n)\right] \\ b^* &= 200\left[f(Y/Y_n) - f(Z/Z_n)\right] \end{aligned}$$

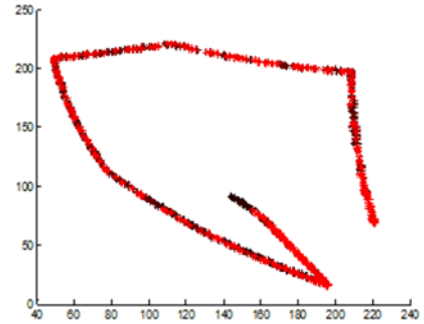
where

$$f(t) = \begin{cases} t^{1/3} & \text{if } t > \left(\frac{6}{29}\right)^3 \\ \frac{1}{3}\left(\frac{29}{6}\right)^2 t + \frac{4}{29} & \text{if } t \le \left(\frac{6}{29}\right)^3 \end{cases}.$$

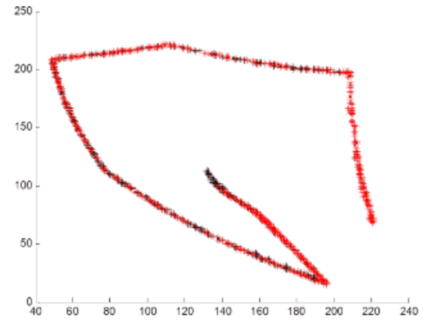
4. Results and discussions

The measured vibration signals and thermography images are shown in Fig. 3. From the thermal images in Fig. 3(b), the differently colored rotor shaft and bearing (in a brighter color than the background color) indicates that heat dissipations are mainly from two bearings and thermal spreading toward connected shafts, resulting in a gradual change in temperature along the distance. However, the measured time signal of the misaligned sample, shown in Figs. 3(c) and (d), presents stable periodic peaks not found under normal conditions [Fig. 3(a)]. Usually, friction that results from mechanical faults is the main factor that generates heat. Therefore, a misaligned shaft and bearing fault can generate more heat around the bearing housing, which can produce a thermal gradient. As shown in Fig. 3(d), a larger color gradient from the left bearing is clearly observed because the bearing is misaligned. An additional fault is shown when the bearing outer race fault of the right bearing gives additional peaks in the time signal with the highest amplitude in Fig. 3(e). The clear difference in color gradient in the right bearing, compared to Fig. 3(d), corresponds to the time signal measurement.

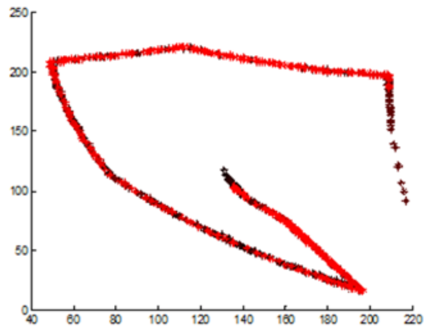
The acquired thermal images were transformed successfully



(a)



(b)



(c)

Fig. 4. a-b plane projections of MFS under (a) normal; (b) misalignment; (c) bearing fault conditions.

from RGB values to CIELab. $L*$ values can be excluded to simplify feature calculation because a thermal image is the distribution of radiation and the radiations from MFS. The background behind the MFS was too distinctive to rule the values out. The $L*$ values in CIELAB were changed to 0, and the (a, b) values of all the pixels in each thermal image could be projected into an a-b plane without any image distortion, as shown in Fig. 4. The dots in Fig. 4 represent the plus values, and the black dots represent the minus values. From the projected patterns, which seem to be similar but are not the same, we can recognize different fault modes by different projected patterns. The pattern for a normal situation in Fig. 4(a) can be distinguished by the other fault modes.

After feature calculation, a large amount of unnecessary information may continue to be contained. Feature extraction is employed to obtain effective features that represent better

(a)

(b)

(c)

Fig. 5. Extracted ROI images from thermal images of MFS under (a) normal; (b) misalignment; (c) bearing fault conditions.

machine conditions. SVMs based on multi-class classification are applied to perform the classification process using OAO and OAA methods. Fig. 5 shows the extracted regions of interest (shaft, bearing, and bearing housing) in different mode conditions. Compared to the normal condition in Fig. 5(a), the extracted images from the processed thermal images can suggest meaningful image shapes, which can be used to diagnose faults for different fault modes without direct measurement.

Therefore, extracting the features of a thermal image can provide a non-contact inspection method for fault analysis, as successfully classified and demonstrated in this study. The performance of OAO classifiers is better than that of OAA classifiers in terms of classification accuracy. The overall success ratios of class classification are 93% for OAA and 95% for OAO testing.

5. Conclusions

The proposed method can be applied with both thermal images and vibration. It shows excellent accuracy levels. The accuracies of classification by thermal images with only three features are 93% to 95% and 96.25% from the classification of vibration signals with over four features. To obtain high accuracy through SVM with thermal images, the parameters must be optimized. In addition, a larger number of image features increases the classification performance. Faster and easier diagnostic techniques to obtain the condition signals were successfully suggested and demonstrated through the non-contact inspection method via thermography. Therefore, this method can be used as an alternative or complementary tool to diagnose the faults of rotating machines through vibration. Moreover, this method is very useful for diagnosing the stator winding problem, which cannot be properly detected early with vibration analysis.

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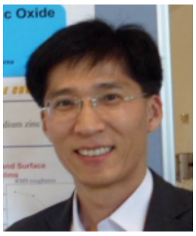

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