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Journal-bearing fault detection based on vibration analysis using feature selection and classification techniques

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ABSTRACT

Vibration technique in a machine condition monitoring provides useful reliable information, bringing significant cost benefits to industry. By comparing the signals of a machine running in normal and faulty conditions, detection of faults like journal-bearing defects is possible. This paper presents an appropriate procedure for the fault detection of main engine journal-bearing based on vibration analysis. The frequency-domain vibration signals of an internal combustion engine (IC engine) with normal and defective main journal-bearings were obtained. The signal processing technique plays one of the important roles for recognizing the journal-bearing fault in the proposed system. In the present research, the data mining method based on feature extraction and selection is proposed. The database is established by the feature vectors of frequency domain signals which are used as input pattern in the training and identification process. The SVM and KNN is proposed to identify and classify the journal-bearing fault conditions in the condition monitoring system. The experimental results verified that the proposed diagnostic procedure has more possibilities and abilities in the fault diagnosis of the main journal-bearing of IC engine.

Introduction

Since the condition monitoring has significant impacts in industry, it has received an enormous attention from the expert and practical maintenance. According to study, maintenance costs are a major part of the total operating costs of all manufacturing, which can make or break a business [1]. Reliability has always been an important aspect in the assessment of industrial products [16]. With the increase in production capabilities of modern manufacturing systems, plants are expected to run continuously for extended hours. Therefore, the condition monitoring of machines, especially early fault diagnosis, is proved to be necessary and has been received wide attentions in this decade [17]. By development of technology, cost of time-based preventive maintenance increased thus, new approaches in maintenance such as condition-based maintenance (CBM) developed [18].

Most of machinery used in the modern world operates by means of rotary components which can develop failures. The monitoring of the operative conditions of rotating machinery provides a great economic improvement by decreasing maintenance costs, as well as improving the safety level. So, it is essential to analyze the external information so as to evaluate the internal components state which, generally, are inaccessible without disassemble the machine [19].

Fault diagnosis is a wide and active area of research. There are a large volume of articles that deal with this subject [2]. In many applications the problem of fault diagnosis is an important issue that has been theoretically and experimentally investigated with different types of methods. Fault diagnosis improves the reliability and availability of an existing system. Since various failures degrade relatively slowly, there is potential for fault diagnosis at an early step [3].

Vibration analysis in particular has been applied for some time as a predictive maintenance method and as a support for machinery maintenance decisions [20]. Vibration analysis provides the most information from the data acquired [5]. Vibration monitoring of rotary machines has become an appealing field for many researchers and has also achieved industrial acceptance [22].

Journal-Bearings are multifunctional devices. In order to operate efficiently and provide long service life, journal-bearings often have to satisfy
several requirements simultaneously. These include:

- Position and support a crankshaft or journal and permit motion with minimum energy consumption;
- Support a fixed load and be able to withstand occasional shock loads;
- Run quietly and suppress externally generated vibrations;
- Resist corrosion under normal service conditions as well as during storage or extended down-time [6].

A crankshaft spinning within a journal bearing is actually separated from the journal bearing's metal facing by an extremely thin film of continuously supplied engine oil that prohibits metal to metal contact (Figure 1).

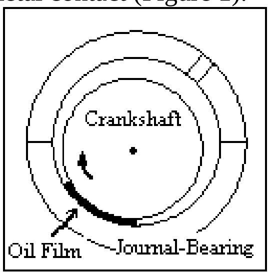

Figure 1. The mechanism of crankshaft motion in journal-bearing

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Journal bearings are applied to carry radial loads, for example, to support a crankshaft of engine. Journal bearings are considered to be sliding bearings as opposed to rolling bearings such as ball bearings. Despite this categorization, a crankshaft spinning within a journal bearing is actually separated from the journal bearing's metal facing by an extremely thin film of continuously supplied engine oil that prohibits metal to metal contact. As such, the journal bearing allows the crankshaft to normally be contacted only by oil, which explains the long life of engines that get regular oil changes. So, the detection and understanding of condition degradation in the journal-bearing is important for engine performance [21].

In this study, a procedure was performed to the detection of journal-bearing fault using vibration analysis. Also, the performance comparison of SVM and KNN was done. Two conditions of the journal-bearing are studied, namely, normal and faulty. The effect of FFT, feature extraction and selection techniques, SVM and KNN classifiers was surveyed. Figure 2 shows flow diagram of the proposed procedure.

Experimental Engine

The experimental system for this work is an internal combustion engine. The working speed of its crankshaft is set at 1500 rpm. Vibration signals were measured for normal and fault conditions by an accelerometer sensor (VMI-102 model) which was mounted horizontally on the crankcase of engine. The frequency-domain signals were gained by X-Viber data acquisition with 8192 Hz sampling rate. The time was 4 second for each sampling. The number of data in each sample was 12800. In this paper, we studied the vibration behavior of the IC engine for normal and defective journal-bearings. Then we estimate the performance of data mining and SVM on classifying the train and test dataset. MATLAB software was used for this work.

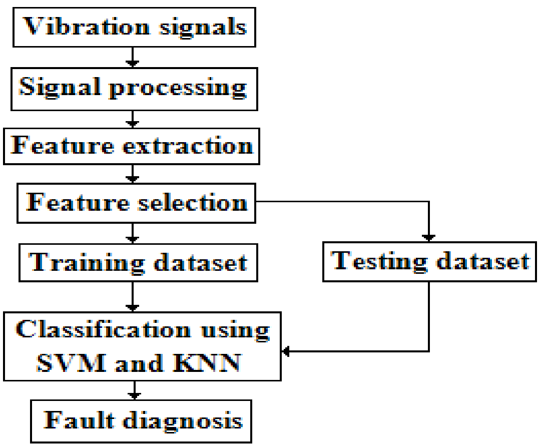

Figure 2. Diagram of diagnostic procedure

Signal Processing

The great advances in vibration analysis in recent years are the extension in signal processing techniques, for vibration diagnostics of journal-bearing defects [6-7-8-9]. The frequency domain spectrum is more useful in identifying the exact nature of fault in the journal-bearings. Although there are various techniques, the analysis of vibration signals is often based on the Fast Fourier Transform (FFT) [10, 23].

The FFT is a faster version of the Discrete Fourier Transform (DFT). The Fourier transform converts waveform data in the time domain into the frequency domain. The Fourier transform implements this by breaking down the original time-based waveform into a series of sinusoidal terms, each with a unique magnitude, frequency, and phase.

The sequence of N complex numbers $x_0,\dots,x_{N-1}$ is transformed into the sequence of N complex numbers $X_0,\dots,X_{N-1}$ by the DFT according to the formula:

$$X_k = \sum_{n=0}^{N-1} x_n e^{-\frac{2\pi i}{N}kn} \quad , \quad k = 0,\dots,N-1 \qquad (1)$$

Data Mining

Feature Extraction

30 features are extracted from time and frequency-domain signals included Maximum, Minimum, Average, Root Mean Square (RMS), Standard Deviation (Stdv), Variance (Var), 4th Momentum, 5th momentum, Crest Factor, Skewness, Kurtosis, etc.

Feature Selection

Stepwise selection is a method that allows moves in direction, dropping or adding variables at the various steps. Forward stepwise selection involves starting off in a forward approach and then potentially dropping variables if they later appear to be not significant. This means that starting with empty the variable set, stepwise forward selection add the variable which leads to the smallest decrease in prediction error. Significance is measured by a partial F-test. In this work the value of p (significance level) is 0.2. In this step 2 features are selected [24].

Support vector machine

The Support Vector Machine (SVM) has been developed by Vapnik and is gaining popularity due to many appealing features, and promising empirical performance.SVM is a popular technique for machine learning activities including classification and regression. The power of SVM in classification leads to abundant application of this in fault detection. SVMs are introduced on the foundation of statistical learning theory [11-12-13]. Support vector machines (SVM) were originally designed for binary (2-class) classification. The SVM tries to place a linear hyperplane between the two different classes [14-15].

The hyperplane can be expressed in following terms:

$$w^T.x + b = \sum_{j=1}^{n} w_j x_j + b = 0 \quad , \quad x = \{1,2,\dots n\} \quad , \quad w \in R^N ,$$

$$b \in R \qquad (2)$$

where the vector w defines the hyperplane, b is a scalar threshold. The equations for class 1 and -1, respectively, are

$$(w.x) + b = 1 \qquad (3)$$

and

$$(w.x) + b = -1 \qquad (4)$$

The following decision function holds good for all data points belonging to either 1 or -1:

$$f(x) = sign((w.x) + b) \qquad (5)$$

The optimal hyperplane can be obtained by solving the optimization problem:

minimize: $\tau(w) = \frac{1}{2}\|w\|^2$ (6)

subject to: $y_i((w.x_i) + b) \ge 1 \;,\; i = 1,\dots,l$ (7)

where l is the number of training sets. The solution of the constrained quadratic programming (QP) optimization problem can be obtained as

$$w = \sum v_i x_i \qquad (8)$$

where x_i are SVs obtained from training. Putting (8) in (5), the decision function is obtained as follows:

$$f(x) = sign(\sum_{i=1}^{l} v_i (x.x_i) + b) \qquad (9)$$

In cases where the linear hyperplane in input spaces will not be enough to separate two classes exactly, it is possible to construct a hyperplane that allows linear separation in the higher dimension (feature space). In SVMs, this is achieved through the use of a mapped function $\phi(x)$ that transforms the data from an N -dimensional input space to Q -dimensional feature space. Substituting the mapping in (9) gives

$$f(x) = sign(\sum_{i=1}^{l} v_i (\phi(x).\phi(x_i)) + b) \qquad (10)$$

The mapping into higher-dimensional feature space is relatively severe computation. A kernel can be used to perform this mapping. It means that the transformation can be replaced by an equivalent kernel function. This helps in reducing the computational load. The kernel function $K(x, y)$ is defined as

$$K(x, y) = \phi(x).\phi(y) \qquad (11)$$

The decision function is accordingly modified as

$$f(x) = sign(\sum_{i=1}^{l} v_i K(x, x_i) + b) \qquad (12)$$

There are different kernel functions like polynomial, quadratic, sigmoid, RBF, multilayer perceptron.
In below, RBF kernel, given by Eq. (13) is described [25].

$$K(x, y) = \exp(\frac{-|x-y|^2}{2\sigma^2}) \text{ , } 0 < \sigma < +\infty \qquad (13)$$

For SVM, QP method and the RBF kernel with σ=1 are used.

K-Nearest Neighbor

Some training samples are used for train the KNN rule. K nearest neighbour rule holds position of training samples and their class. When decision about new incoming data is needed, distance between query data and training samples is being calculated. Based on the defined threshold for the rule (it is the K number), K samples with least distances is selected and the class with more samples inbound is the result. In the other word, for example if there is 2 or 3 features for a classification situation, position of training samples and input sample can be visualized on 2D and 3D

Cartesian coordinates. Process to find result is like to draw a circle (Sphere) centred on input location and increase radius until k samples are embed inside the circle (sphere) and then a class with more samples inbound is the result.

Without prior knowledge, the KNN classifier usually applies Euclidean distances as the distance metric. However, this simple and easy-to-implement method can still yield competitive results even compared to the most sophisticated machine learning methods [26]. The Euclidean distance between point p and q is the length of the line between them.

Results and Discussion

The aim of this paper is the journal-bearing fault diagnosis of engine. To fulfill this purpose, FFT signal processing, data mining technique, SVM and KNN classifiers were used.

Figure 3 and 4 shows the spectrum analysis of the normal and faulty journal-bearing. It is obvious that the overall vibration amplitude of journal-bearing for faulty condition is more.

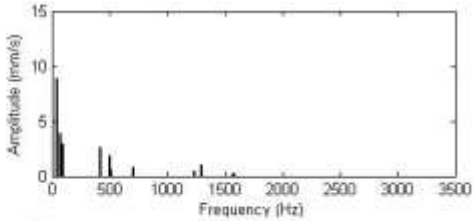

Figure 3. Frequency spectrum of normal journal-bearing

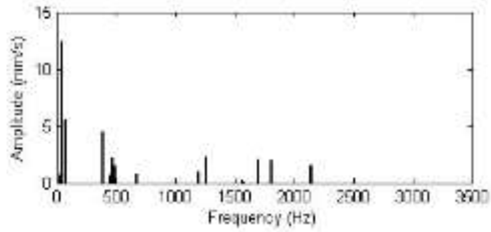

Figure 4. Frequency spectrum of defective journal-bearing

The data mining process is significantly effective in classification results. 30 features were extracted from the vibration signals in frequency-domain. Then 2 superior features were selected by the Stepwise Backward Selection technique with p value of 0.05 and linear model. The dataset consisting of 2 features and 40 samples were divided into two subsets, training set and test set. The SVM classifier was trained by training dataset, and then their performance was exactly estimated by the test dataset.

For SVM, the target values were specified as 1 and -1, respectively, representing normal and defective journal-bearing. The SVM with RBF kernel width of 1 (σ) and QP method were applied for this work. Figure 5 shows the classification result of journal-bearing conditions. The train and test success of the SVM was 95% and 93%. So, it can be found that the performance of proposed procedure was perfect in the fault diagnosis of main engine journal-bearing.

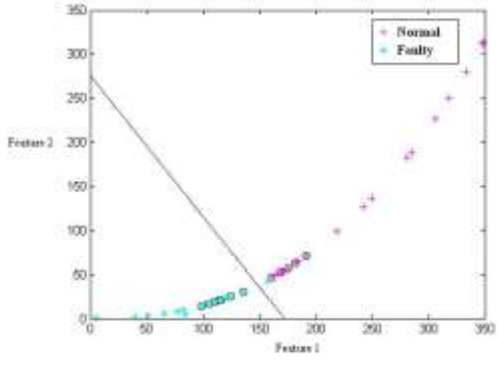

Figure 5. The classification of normal and defective journal-bearing by using SVM

KNN is a classifier that its accuracy is always 100% on training dataset, because the KNN holds the position of training dataset and their class during the classification process. The test success of the KNN just depends on the K value. The K value of 1 was used for the KNN. The performance of KNN was 89.84%.

By attention to the results, it can be found that the performance of SVM was significantly better than KNN in the fault detection of main engine journal-bearing.

Conclusion

A procedure was presented for the fault diagnosis of main journal-bearing in IC engine by using the data mining technique and Support vector Machine classifier. The Fast Fourier Transform technique is applied for processing signals. The features of the generator output signal at different journal-bearing conditions are extracted by the statistical and vibration parameters. To further diminish the dimensionality of the extracted feature vectors and enhance the model performance, stepwise backward selection was used. Finally, the feature vectors are fed into the SVM and KNN. The performance of SVM is calculated by applying RBF kernel and Quadratic Programming method. KNN with K=1 and Euclidean distance was used. The results of recognition rates are used to estimate the work efficiency in the proposed system. The FFT and SVM techniques can provide good diagnosis efficiency for fault journal-bearing positions identification and journal-bearing fault conditions classification, respectively. The total recognition rates are over 93%. Therefore, the results indicated that the proposed system can provide an accurate and automatic diagnosis technique for the journal-bearing of IC engines.

Acknowledgement

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