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# Condition monitoring of engine journal-bearing using power spectral density and support vector machine

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**ABSTRACT**

Recently, the issue of machine condition monitoring became global due to the potential advantages to be obtained from decreased maintenance costs, improved productivity and increased machine availability. 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 fault like journal-bearing defect is possible. This paper deal a new method of engine journal-bearing fault diagnosis based on Power Spectral Density (PSD) of vibration signals in combination with Support Vector Machine (SVM). The frequency domain vibration signals of an internal combustion engine (IC engine) with three main journal-bearing conditions were gained, corresponding to, (i) normal, (ii) corrosion and (iii) excessive wear. The features of PSD values of vibration signals were extracted using statistical and vibration parameters. The extracted features were used as inputs to the SVM for three-class identification. The roles of PSD technique and SVM classifier were investigated. Results showed that the accuracy rate of fault diagnosis of the IC engine main journal-bearing was 100%. The results demonstrate that the proposed method has the potential for fault diagnosis of main journal-bearing of IC engine.



## Introduction

Condition monitoring provides significant information on the health and maintenance requirement of rotary machinery and is used in a vast range of industrial applications [1]. The condition monitoring, diagnostic systems are mainly used to any machines based on vibration and technological parameters measurements [2]. Parameters such as vibration, temperature, lubricant quality and acoustic emission can be used to monitor the mechanical status of equipment. In general, fault diagnosis is a wide and active area of research. There are a large volume of articles that deal with this subject [1].

Most of machinery used in the modern world operates by means of rotary parts which can develop faults. The monitoring of the operative conditions of a rotary machine provides a great economic improvement by reducing maintenance costs, as well as improving the safety level. As a part of the machine maintenance task, it is necessary to analyze the external information in order to evaluate the internal components state which, generally, are inaccessible without disassemble the machine [3].

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. This avoids the sudden, total system failure which can have serious consequences. Fault diagnosis provides more information about the nature or localization of the failure. This information can be used to minimize downtime and to schedule adequate maintenance proceeding.

In recent years, on-line fault diagnostic systems have been gaining considerable amount of business potential. The need for automating industrial processes and reducing the cost maintenance has simulated the research and extension of faster and robust fault diagnosis. Attempts have been created towards classification of the most common type of rotating machinery problem [4].

Vibration analysis is one of the main techniques used to diagnose and predict various defects in journal-bearing [5]. Vibration analysis provides early information about progressing malfunctions for future monitoring purpose.

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;
- Act as a guide to support reciprocating or oscillating motion;
- Withstand temperature excursions;
- Accommodate some degree of crankshaft misalignment;
- Accommodate dirt particles trapped in the lubricant;
- 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.

Defective journal-bearing can alter the thickness of oil film. This will lead to changing normal movement of the crankshaft. So, failure journal-bearing increase vibration of crankcase at rotational speed of the crankshaft.

Common techniques used for journal-bearing fault detection include time and frequency domain analyses. Statistical

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information of the time domain signal can be applied as trend parameters. They can provide information such as the energy level of the vibration signals and the shape of the amplitude probability distributions.

Other than focussing on the time domain signal, spectrum analysis provides spectrum in the frequency domain. The spectrum peaks in fault condition can be compared with spectrum peaks of normal journal-bearing to determine whether the journal-bearing is experiencing a particular fault [7].

The spectrum analysis was based on the Fast Fourier Transform (FFT) [8-9]. This approach suffers from some limitations. Among these limitations, the FFT is not efficient to describe the non-stationarities introduced by faults in the vibration signal. The second limitation and the most important one is the frequency resolution, which is the ability to distinguish the spectral responses to two or many harmonics. Another limitation is due to the windowing of data which appears during the FFT processing. In order to overcome these performance limitations inherent to the FFT approach, many modern spectral estimation techniques have been proposed during the last two decades [10-11]. Power spectral density (PSD) is one of those methods.

The Support Vector Machines (SVMs) have been introduced by Vapnik in 1960s. Support Vector Machine (SVM) is a powerful learning machine based on the statistical learning theory which is mostly applied for classification purposes [12]. Support Vector Machine performs machine condition monitoring and diagnosis by using its unique ability in classification process. It is to be stressed here that SVM becomes popular and prominent in machine learning community due to the excellence of generalization ability than the traditional method such as neural network.

In the present work, a procedure is implemented to the detection of journal-bearing faults using vibration analysis. Three conditions of the journal-bearing are studied, namely, normal, corrosion and excessive wear conditions. The effect of PSD and feature extraction technique and SVM classifier is surveyed. Finally, the method success is calculated in fault diagnosis of engine journal-bearing.

**Experimental System**

The case study for this work was a 4 cylinder internal combustion engine with power of 125 hp. Vibration signals were collected for normal, corrosion and excessive wear conditions of main journal-bearing. Faulty journal-bearings were selected from the IC engine that was worked for a long time periods and their faults led to reduce of their efficiencies. The working speed of the engine crankshaft was set at approximately 1500 rpm.

The vibration signals in frequency-domain were measured by an accelerometer. Then, Root Mean Square (RMS) of vibration acceleration (g) was calculated for these signals. The accelerometer (VMI-102 model) was mounted horizontally on the crankcase of engine ahead main journal-bearing exactly. The sensor was connected to the signal-conditioning unit (X-Viber FFT analyzer), where the signal goes through a charged amplifier and an analogue-to-digital converter (ADC). The software SpectraPro-4 that accompanies the signal-conditioning unit was used for recording the signals directly in the computer. The sampling rate was 8192 Hz and the number of data in each sample was 12800.

**Power Spectral Density (PSD)**

Power spectral density (PSD) function indicates the vigor of the variations (energy) as a function of frequency. In other words, it indicates at which frequencies variations are powerful and at which frequencies variations are weak [3-13].

The complex spectrum of a vibration *x(t)* in the time range *($t_1$, $t_2$)* for any frequency *f* in the two-sided frequency domain *(-F, +F)* can be expressed as:

$$X(f) = \int_{f_1}^{f_2} x(t) e^{-2\pi i f t} dt \qquad (1)$$

If *x(t)* is stated in units of *($m/s^2$)*, *X(f)* is stated in units of *($m/s^2$)/Hz*. From the complex spectrum, the one-sided power spectral density can be calculated in *$(m/s^2)^2/Hz$* as:

$$PSD(f) = \frac{2|X(f)|^2}{(t_2 - t_1)} \qquad (2)$$

Where the factor *2* is due to adding the contributions from positive and negative frequencies. The *PSD* divides up the total power of the vibration. We integrate it over its entire one sided frequency domain *(0, F)*:

$$\int_0^f PSD(f) df = \frac{\int_{f_1}^{f_2} |x(t)|^2 dt}{(t_2 - t_1)} \qquad (3)$$

The result is exactly the average power of the vibration in the time range *($t_1$, $t_2$)*. If *FFT* of vibration signal be applied, *PSD* can be computed directly in the frequency domain by following formula:

$$PSD = \frac{g_{rms}{}^2}{f} \qquad (4)$$

where $g_{rms}$ is the Root Mean Square of acceleration in a certain frequency *f* [14-15].

**Feature Extraction**

The PSD values of the signals were calculated to obtain the most significant features by feature extraction technique. The feature extraction directly affects the final diagnosis results. In this work, 30 features extracted from PSD values of the vibration signals using statistical and vibration parameters. Some of the used parameters are: Maximum, Minimum, Average, Root Mean Square (RMS), Standard Deviation (Stdv), Variance (Var), 5th Momentum (5th M), sixth momentum (6thM), Crest Factor, Skewness, Kurtosis, etc [16-17].

**Support Vector Machine (SVM)**

The Support Vector Machines (SVM) have been developed by Vapnik and are gaining popularity due to many appealing features, and promising empirical performance. SVM, based on statistical learning theory, is a proper technique for solving a variety of learning and function assessment problems. SVM have been successfully applied to a number of applications such as machine condition monitoring, face detection, verification, and recognition, object detection and recognition, handwritten character and digit recognition, text detection and categorization, speech and speaker verification, recognition, information and image retrieval, etc. Support vector machines (SVM) were originally designed for binary (2-class) classification [18]. In binary classification, the class labels can take only two values: 1 and -1. Figure 1 shows the classification of binary SVM.

SVM has been recently applied to solve multi-class problems. Many researches have been done on developing 2-class SVM into multi-class SVM such as [19].

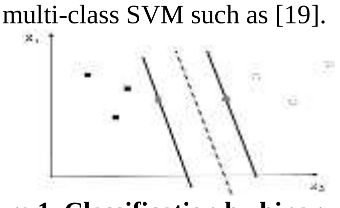

**Figure 1. Classification by binary SVM**

**Binary SVM**

Suppose label the training data $\{x_i, y_i\}, i = 1,...,l$, $y_i \in \{-1,1\}, x_i \in R^d$. There are some hyperplane that separates the positive (class +1) from the negative (class -1) examples. The vector $x$ which lie on the separating hyperplane satisfy $w.x + b = 0$, where $w$ is normal to the hyperplane. In the separable case, all data satisfy the following constraints:

$$w.x_i + b \geq +1, \; y_i = +1 \quad (5)$$

$$w.x_i + b \leq -1, \; y_i = -1 \quad (6)$$

These can be combined into the following inequalities:

$$y_i(w.x_i + b) - 1 \geq 0 \;\; \forall i \quad (7)$$

$d_+(d_-)$ is the shortest distance from the separating hyperplane to the closest positive (negative) training data. The margin of a separating hyperplane is defined to be $d_+ + d_-$. By constraints Eq.(5) and Eq.(6), $d_+ = d_- = 1/\|w\|^2$ and the margin is simply $2/\|w\|^2$. Thus we can find the separating hyperplane which gives the maximum margin by minimizing $\|w\|^2$, subject to constraints Eq.(7). Using the Lagrange multiplier technique, a positive Lagrange multipliers $\alpha_i, i = 1,...,l$, one for each of the inequality constraints Eq.(7) is determined. This gives Lagrangian:

$$\min \mathrm{l}_p = \frac{1}{2}\|w\|^2 - \sum_{i=1}^{l} \alpha_i y_i (x_i.w + b) + \sum_{i=1}^{l} \alpha_i$$

$$\alpha_i \geq 0 \quad (8)$$

In order to deal properly with nonlinear SVM, $\mathrm{l}_p$ is transformed into dual problem:

$$\max \mathrm{l}_p = \sum_i \alpha_i - \frac{1}{2}\sum_{i,j} \alpha_i \alpha_j y_i y_j (x_i.x_j)$$

$$\alpha_i \geq 0 \quad (9)$$

$$\sum_{i=1}^{l} \alpha_i y_i \geq 0$$

In the case where the data cannot be separated by hyperplane without errors, Vapnik propose that introducing positive slack variables $\xi_i, i = 1,...,l$, the constraints become:

$$w.x_i + b \geq +1 - \xi_i \;\; \text{for} \;\; y_i = +1 \quad (10)$$

$$w.x_i + b \leq -1 + \xi_i \;\; \text{for} \;\; y_i = -1 \quad (11)$$

$$\xi_i \geq 0 \quad (12)$$

The goal is to build hyperplane that makes the smallest number of errors. Hence the objection function becomes

$$\text{minimize:} \; \|w\|^2 / 2 + C(\textstyle\sum_i \xi_i) \quad (13)$$

where $C$ is penalty parameter, a larger $C$ corresponding to assigning a higher penalty to errors. The $C$ must be chosen by the user. The optimization problem becomes:

$$\max \mathrm{l}_D = \sum_i \alpha_i - \frac{1}{2}\sum_{i,j} \alpha_i \alpha_j y_i y_j (x_i.x_j)$$

$$0 \leq \alpha_i \leq C \quad (14)$$

$$\sum_i \alpha_i y_i \geq 0$$

Suppose that the data is mapped to a higher dimension space (feature space), using a mapping which is called $\phi$

$$\phi : R^d \rightarrow F \quad (15)$$

Then the training algorithm would only depend on the data through dot products in $F$, i.e. on functions of the from $\phi(x_i).\phi(x_j)$. Kernel function is the significant concept of SVM, The definition of kernel is:

$$k(x_i.x_j) = \phi(x_i).\phi(x_j) \quad (16)$$

In below, the formulation of three kernels is given:

Linear: $k(x_i.x_j) = x_i.x_j$

Polynomial: $k(x_i.x_j) = (\gamma x_i.x_j + 1)^d, \gamma > 0$ (17)

Gaussian RBF: $k(x_i.x_j) = \exp\left(\dfrac{-\|x_i - x_j\|^2}{2\sigma^2}\right)$

So the optimization problem of nonlinear SVM is:

$$\max \mathrm{l}_D = \sum_i \alpha_i - \frac{1}{2}\sum_{i,j} \alpha_i \alpha_j y_i y_j k(x_i.x_j)$$

$$0 \leq \alpha_i \leq C \quad (18)$$

$$\sum_i \alpha_i y_i \geq 0$$

After solving this optimization problem, those points for which $\alpha_i > 0$ are called 'support vectors'. Then they determine $w$ by Eq.(19). And $b$ can be found by KKT 'complementarily' condition Eq.(20), where $s_i$ are support vectors and $N_s$ is the number of support vectors.

$$w = \sum_{j}^{N_s} \alpha_j y_j \phi(s_j) \quad (19)$$

$$\alpha_i (y_j (w.\phi(s_j) + b) - 1) = 0 \quad (20)$$

Finally, the class of $x$ is:

$$sign(w.x + b) = sign\left(\sum_{j}^{N_s} \alpha_j y_j k(s_j, x) + b\right) \quad (21)$$

**Multi-class SVM**

In the real world, we deal more than two classes for examples: in condition monitoring of rotating machineries there are several classes such as journal-bearing faults, mechanical unbalance, misalignment, different load conditions, gear faults etc. There are different methods for multi-class SVM such as one-against-all (OAA), one-against-one (OAO), etc [20-21]. In this paper OAA method was used. Therefore, in next section the one-against-all multi-class method (OAA) will be discussed.

**One-against-all (OAA)**

The OAA method is earliest implementation for SVM multi-class classification. It builds $k$ SVM models where $k$ is the number of classes. The $i$th SVM is trained with all of examples in the $i$th class with positive labels, and all the other examples with negative labels. Thus given $l$ training set $(x_1, y_1),...,(x_l, y_l)$, where $x_i \in R^n, i = 1,...,l$ and $y_i \in \{1,...,k\}$ is the class of $x_i$, the $i$th SVM solve the following problem:

$$\text{minimize:} \; \frac{1}{2}\|w^i\|^2 + C\sum_{i=1}^{1} \xi_j^{\,i} (w^i)^T \quad (22)$$

subject to:

$$(w^i)^T \phi(x_j)+b^i \ge 1-\xi_j^{\,i} \quad \text{if} \quad y=i$$
$$(w^i)^T \phi(x_j)+b^i \le -1+\xi_j^{\,i} \qquad \text{if} \qquad y \ne i \qquad (23)$$
$$\xi_j^{\,i} \ge 0 \;\; , \;\; j=1,\ldots,l$$

where the training data $x_i$ is mapped to a higher-dimensional space by function $\phi$ and $C$, is the penalty parameter and $\xi$, is the slack variable.

Minimizing Eq. (22) means to maximize $2/\|w_i\|$. When data is not separable, there is a penalty term $C\sum_{i=1}^{l}\xi_{i,i}$, which can reduce the number of training errors.

Finally, $x$ is in the class which has the largest value of the decision function $w^T\phi(x)+b$.

We have implemented these methods by using SVM Toolbox. The software is available at http://asi.insa-rouen.fr/~gloosli/simpleSVM.html

**Results and Discussion**

Figure 2 shows the samples of PSD diagram of vibration signals acquired for different conditions of the journal-bearing. By attention to this Figure, it can be seen that the maximum value of PSD is increased by increasing the severity of journal-bearing faults.

30 features were extracted from the PSD values for three conditions of journal-bearing. Dataset for each class were divided into two parts, training and test dataset. Finally, SVM generated by training with train dataset and simultaneously simulated by test dataset.

We considered the penalty parameter $C$ of $10^3$, condition parameter of QP method (lambda=$10^{-7}$) and RBF kernel for SVM.

Simulation results showed that, the accuracy rate of SVM with OAA multi-class method was 100% on both training and test set. This accuracy was occurred in RBF kernel width of 1 ($\sigma$=1).

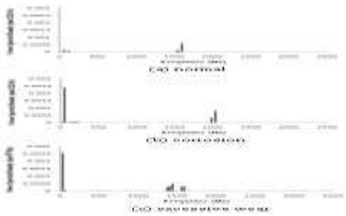

**Figure 2. PSD- Frequency diagrams of journal-bearing in three conditions**

By attention to this result, it can be found that the PSD is the one of useful signal processing technique. Also, using enough and correct features could will result in powerful inputs for classifier and raise its diagnosis accuracy. Gaining the excellent performance indicate proper selection of SVM classifier and its parameters.

**Conclusion**

A combined Power Spectral Density (PSD) and Support vector Machine (SVM) have been presented to perform fault diagnosis of main journal-bearing of an internal combustion engine. Three states of journal-bearing was detected, namely, normal, corrosion and excessive wear. Firstly, PSD values of the vibration signals were calculated from obtained spectrums for three journal-bearing conditions. Secondly 30 features were extracted from PSD values as inputs to classifier. Finally, the structure of SVM classifier with one-against-all (OAA) multi-class method is built by feeding the training dataset and then its performance was estimated by test dataset. The classification accuracy of three conditions of journal-bearing was 100% on both training and test dataset. The results show that the SVM is a strong classifier for fault diagnosis of rotary machine. Also, the results demonstrate the ability and reliability of proposed PSD-SVM model in condition monitoring of engine journal-bearing.

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