814. Fault diagnosis of main engine journal bearing based on vibration analysis using Fisher linear discriminant, K-nearest neighbor and support vector machine

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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 defected journal bearings is possible. This paper presents fault diagnosis of a journal bearing based on vibration analysis using three classifiers: Fisher Linear Discriminant (FLD), K-Nearest Neighbor (KNN) and Support Vector Machine (SVM). The frequency-domain vibration signals of an internal combustion engine with intact and defective main journal bearings were obtained. 30 features were extracted by using statistical and vibration parameters. These features were used as inputs to the classifiers. Two different solution methods - variable K value and RBF kernel width (σ) were applied for FLD, KNN and SVM, respectively, in order to achieve the best accuracy. Finally, performance of the three classifiers was calculated in journal bearing fault diagnosis. The results demonstrated that the performance of SVM was significantly better in comparison to FLD and KNN. Also the results confirmed the potential of this procedure in fault diagnosis of journal bearings.

Keywords: condition monitoring, fault diagnosis, Fisher linear discriminant, K-nearest neighbor, support vector machine, engine main journal bearing.

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]. In many applications the problem of fault diagnosis is an important issue that has been theoretically and experimentally investigated with different types of methods.

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 [31]. 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 of the machine [3].

Fault diagnosis improves the reliability and availability of an existing system [30]. 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 of maintenance has stimulated the research and extension of faster and robust fault diagnosis. Attempts have been made towards classification of the most common type of rotating machinery problem [4].

Vibration analysis is one of the main techniques used to the non-destructive diagnosis and identification of various defects in rotary machines [5-32]. 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 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 (Fig. 1).

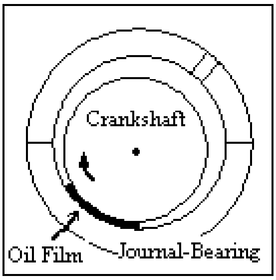

Fig. 1. The mechanism of crankshaft motion in journal bearing

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 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 focusing 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].

In this research, the vibration signals in frequency domain were acquired under different main journal bearing conditions in the internal combustion engine. The statistical and vibration features of the signals were extracted for the classification of the journal bearing conditions. Also, we compared the ability of three classifiers in fault diagnosis, because the superior method should be known. Fig. 2 presents the diagram of the proposed procedure for fault diagnosis.

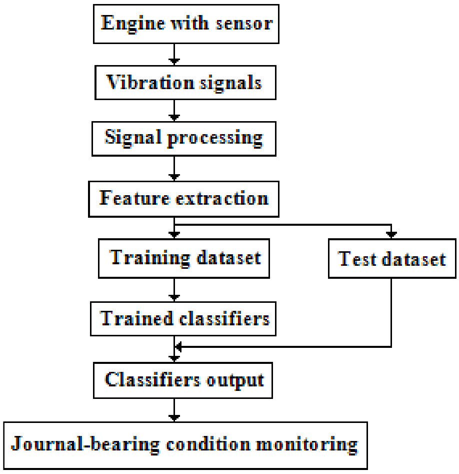

Fig. 2. The schematic of proposed approach

Experimental System

The experimental system consists of an internal combustion engine with power of 145 kW. The working speed of its crankshaft was set at 1500 rpm.

The location of the sensor plays a considerable role in fault diagnosis. Due to space limitation and special form of engine, the sensor can be just mounted horizontally on the crankcase in front of the main journal bearing. The sensor used was a piezoelectric accelerometer (VMI-102 model) for measuring the signals. The sensor was connected to signal-conditioning unit (X-Viber FFT analyzer). Single channel vibration analyzer was used for measuring vibration response of the engine. The frequency domain signals were measured for normal and faulty journal bearings with sampling rate of 8192 Hz. The software SpectraPro-4 that accompanies the signal-conditioning unit was used for recording the signals directly in the computer.

The great advances in vibration analysis in recent years are the extension in signal processing techniques, for vibration diagnostics of journal bearing defects [8-9-10-11]. The time and frequency domain analyses are widely accepted for detecting malfunctions in journal bearings. The frequency domain spectrum is more useful in identifying the exact nature of fault in the journal bearings [12]. Although there are various techniques, the analysis of vibration signals is often based on the Fast Fourier Transform (FFT) [13].

In this paper, the vibration behavior of the engine for the normal and defective journal bearings was studied. The sensor was located at horizontal direction on the crankcase near the journal bearing. The root mean square (RMS) of the vibration velocity (mm/sec) was calculated for the frequency domain signals. The statistical and vibration parameters were used for extracting features from the frequency domain signals. Then three types of classification were performed for identifying two different conditions, namely, Fisher Linear Discriminant, K-Nearest Neighbor and Support Vector Machine. MATLAB software was used for analyzing the data.

Signal Processing

Signal processing techniques have been widely used to extract fault features from vibration signals. Fast Fourier Transform (FFT) has been the dominating analysis tool for feature

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extraction of stationary signals. 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 [14]. The transformation of time domain signals into frequency domain was performed by X-Viber FFT analyzer.

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

$$X_k = \sum_{n=0}^{N-1} x_n e^{-\frac{2\pi i}{N}kn}, \qquad k = 0,...,N-1. \tag{1}$$

Feature Extraction

The feature extraction straightly affects fault diagnosis results. In this paper, 30 features were extracted from RMS values of vibration velocity of signals by using the statistical and vibration parameters. They included Maximum, Minimum, Average, Standard Deviation (Stdv), Variance (Var), 4th central moment, 5th central moment, Skewness, Kurtosis, etc. Many of these parameters were used in [15-16-17]. Some of these features are explained below.

Minimum: it is the minimum signal point values.

Maximum: it is the maximum signal point values.

Average: it is the average of all signal point values.

Standard deviation: This is a measure of the effective energy or power content of the vibration signal:

$$Stdv = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{2}$$

Variance: It is variance of the signal points:

$$Variance = \frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n} \tag{3}$$

Skewness characterizes the degree of asymmetry of a distribution around its mean:

$$Skewness = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^3}{(\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2)^{3/2}} \tag{4}$$

Kurtosis indicates the flatness or the spikiness of the signal:

$$Kurtosis = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^4}{(\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2)^2} - 3. \tag{5}$$

Fisher Linear Discriminant (FLD)

Fisher linear discriminant is a method applied in statistics, pattern recognition and machine learning to find a linear combination of features which separates two or more classes. The FLD results can be used as a classifier in fault detection applications to distinguish different fault conditions of rotary machines. We used the ability of FLD in our research.

FLD method tries to shape the scatter in order to make it more successful for classification [18]. It is a famous linear dimensionality reduction method, optimal in terms of maximizing the separation between two classes [19-20-21].

Supposing the input is a set $\{(x_1, y_1),...(x_l, y_l)\}$ with labeled $y_i \in \{1,2\}$ training inputs $x_i \in R_n$. $I_y = \{i : y_i = y\}$, $y \in \{1,2\}$ be indices of training inputs belonging to the first $y = 1$ and the second $y = 2$ class, respectively. FLD utilizes the label information in finding informative projections by maximizing the following objective:

$$F(w) = \frac{w^T \cdot S_B w}{w^T \cdot S_W w} \tag{6}$$

where S_B is the between classes scatter matrix:

$$S_B = (\mu_1 - \mu_2)(\mu_1 - \mu_2)^T , \qquad \mu_y = \frac{1}{I_y} \sum_{i \in I_y} x_i \tag{7}$$

and S_W is the within classes scatter matrix:

$$S_W = \sum_{i \in I_y} (x_i - \mu_y)(x_i - \mu_y)^T \tag{8}$$

In FLD, the parameter vector w of the linear discriminant function $f(x) = w{\cdot}x+b$ is determined to maximize the class separability criterion:

$$w = \max_{w'} \frac{w'^T \cdot S_B w'}{w'^T \cdot S_W w'} \tag{9}$$

The bias b of the linear rule can be determined by:

$$(w \cdot \mu_1) + b = -((w \cdot \mu_2) + b) \tag{10}$$

Equation (9) can be solved using the two following methods:

1) matrix inversion

$$w = S_w^{-1}(\mu_1 - \mu_2) \tag{11}$$

2) reformulating as the quadratic programming (QP)

$$w = \min_{w'}(w' \cdot S_W w')$$

subject to $(w' \cdot (\mu_1 - \mu_2)) = 2$. (12)

K-Nearest Neighbor (KNN)

When full knowledge of the underlying probabilities of a class of samples is available Bayesian theory gives optimal new sample classification rates. In cases where this information is not present, many algorithms make use of the similarity among samples as a means of classification. The Nearest Neighbor decision rule has often been applied in these patters recognition problems [33]. K-nearest neighbor (KNN) decision rule has been a ubiquitous classification method with good scalability. Many researchers have used KNN for pattern classification applications [34]. K-Nearest Neighbor 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) centered on input location and increase radius until K samples are embedded inside the circle (sphere) and then a class with more samples inbound is the result. Fig. 3 illustrates this method. For $K = 3$, inside small circle there are 2 triangles and 1 square, the result is tri-angle class. For $K = 5$, inside large circle there are 3 squares and 2 tri-angles so the result is square class.

Without prior knowledge, the KNN classifier usually applies Euclidean distances as the distance metric. Although many researchers have performed investigations to develop the Euclidean distances [22], this simple and easy-to-implement method can still yield competitive results even compared to the most sophisticated machine learning methods [23-24]. The Euclidean distance between point p and q is the length of the line between them. In Cartesian coordinates, if p_i and q_i are two points in Euclidean n-space, then the distance from p to q is given by:

$$d_E = \sqrt{\sum_{i=1}^{n} (p_i - q_i)^2} \ . \qquad (13)$$

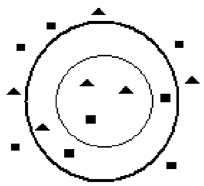

Fig. 3. KNN algorithm for a situation with 2 class and 2 features

Support Vector Machine (SVM)

The Support Vector Machine (SVM) has been developed by Vapnik and is gaining popularity due to many appealing features, and promising empirical performance. SVM, based on statistical learning theory, is an appropriate procedure for solving a variety of learning and function evaluation problems. Support Vector Machine is supervised Machine Learning technique. This is a classification and regression prediction technique that applies Machine Learning theory to maximize predictive accuracy while automatically keeping away from over-fitting. The formulation embodies of SVM is Structural Risk Minimization (SRM) principle [25-26-27]. SRM minimizes an upper bound on the expected risk. That is which SVM has a greater potential to generalizes. SVM has many 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 [35]. SVM was originally designed for binary (2-classes) classification problem which the dataset are separated by a hyperplane defined by support vectors [28-29]. Support vectors are the closest data used to define the margin. In Fig. 4 a series of points for two different classes of data are provided. The SVM tries to place a hyperplane between the two different classes, with maximum margin.

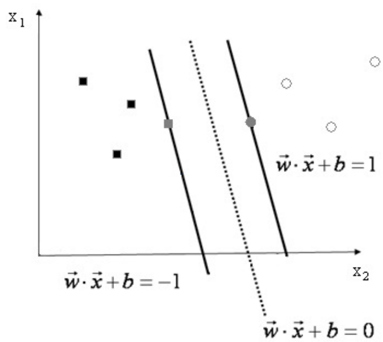

Fig. 4. Classification of data by SVM

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 lies on the separating hyperplane satisfies $w \cdot x + b = 0$, where w is the normal to the hyperplane. In the separable case, all data satisfy the following constraints:

$$w \cdot x_i + b \geq +1 , \quad y_i = +1 \tag{14}$$

and

$$w \cdot x_i + b \leq -1 , \quad y_i = -1 \tag{15}$$

These can be combined into the following inequalities:

$$y_i(w \cdot x_i + b) - 1 \geq 0 \qquad \forall i \tag{16}$$

$d_+ (d_-)$ 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 equation (14) and equation (15), $d_+ = d_- = 1/\|w\|^2$ 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 equation (16). Using the Lagrange multiplier technique, positive Lagrange multipliers α_i, $i = 1,...,l$, one for each of the inequality constraints equation (16) is determined. This gives Lagrangian:

$$\min \ell_p = \frac{1}{2}\|w\|^2 - \sum_{i=1}^{l} \alpha_i y_i (x_i \cdot w + b) + \sum_{i=1}^{l} \alpha_i , \quad \alpha_i \geq 0 \tag{17}$$

In order to deal properly with nonlinear SVM, ℓ_p is transformed into dual problem:

$$\max \ell_p = \sum_i \alpha_i - \frac{1}{2}\sum_{i,j} \alpha_i \alpha_j y_i y_j (x_i \cdot x_j) , \quad \alpha_i \geq 0 , \quad \sum_{i=1}^{l} \alpha_i y_i \geq 0 \tag{18}$$

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

$$\begin{aligned} & w \cdot x_i + b \geq +1 - \xi_i \quad \text{for} \quad y_i = +1 \\ & w \cdot x_i + b \leq -1 + \xi_i \quad \text{for} \quad y_i = -1 \\ & \xi_i \geq 0 \end{aligned} \tag{19}$$

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

$$\text{minimize: } \|w\|^2 / 2 + C(\textstyle\sum_i \xi_i) \tag{20}$$

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:

$$\max \ell_D = \sum_i \alpha_i - \frac{1}{2}\sum_{i,j} \alpha_i \alpha_j y_i y_j (x_i \cdot x_j) , \ 0 \leq \alpha_i \leq C , \ \sum_i \alpha_i y_i \geq 0 \tag{21}$$

Suppose that the data is mapped to a higher dimension space (feature space), using a mapping which is called ϕ:

$$\phi : R^d \to F \tag{22}$$

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

$$k(x_i . x_j) = \phi(x_i) \cdot \phi(x_j) \tag{23}$$

In below, the formulation of three kernels is given:

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

Polynomial: $k(x_i \cdot x_j) = (\gamma x_i \cdot x_j + 1)^d$, $\gamma > 0$ (24)

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

So the optimization problem of nonlinear SVM is:

$$\max \ell_D = \sum_i \alpha_i - \frac{1}{2}\sum_{i,j} \alpha_i \alpha_j y_i y_j k(x_i \cdot x_j), \quad 0 \le \alpha_i \le C, \quad \sum_i \alpha_i y_i \ge 0 \tag{25}$$

After solving this optimization problem, those points which $\alpha_i > 0$ are called support vectors. Then they determine w by equation (26). Also, b can be found by KKT complementarily condition equation (27), where s_j are support vectors and N_s is the number of support vectors:

$$w = \sum_j^{N_s} \alpha_j y_j \phi(s_j) \tag{26}$$

$$\alpha_i (y_j (w \cdot \phi(s_j) + b) - 1) = 0 \tag{27}$$

Finally, the class of x is:

$$\mathrm{sign}(w \cdot x + b) = \mathrm{sign}\left(\sum_j^{N_s} \alpha_j y_j k(s_j, x) + b\right). \tag{28}$$

Fault Diagnosis

The aim of this paper is the condition monitoring and fault detection of the journal bearing of IC engine. To fulfill this purpose, the fault diagnosis system which consists of a combination of signal processing, feature extraction and fault classification, was used. The classification of the journal bearing based on its situation was done using the features extracted from the frequency domain signals. The vibration signals of the frequency domain were obtained for the normal and defective journal bearings by X-Viber FFT analyzer.

Figs. 5-6 provide the frequency spectrum of the vibration signals acquired for the various experimental conditions of the journal bearing. The overall vibrations of journal bearing were higher than the normal values. The results indicated that the overall vibration values of engine were on warning status. So, it revealed that there was a journal bearing defect developing. A developing journal bearing defect was consistent with inadequate lubrication, resulting in an increase of metal-to-metal contact.

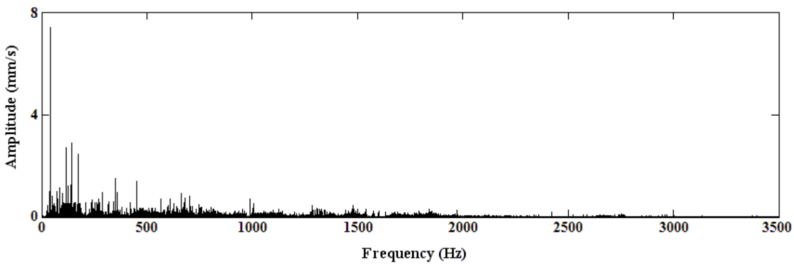

Fig. 5. Frequency spectrum of normal journal bearing

The feature extraction process is significantly effective in classification results. 30 features extracted from the vibration signals were used as inputs to the classifiers. The whole dataset was divided into two subsets, training dataset and test dataset. The classifiers were trained by the training dataset, and then their performance was exactly estimated by the test dataset. Also, their accuracy rate was compared thoroughly. There are three criteria to determine the test performance of classifiers, namely, sensitivity, specificity and total classification accuracy. We reported results according to total classification accuracy. These criteria are defined as:

- Sensitivity: number of true positive decisions/number of actually positive cases.
- Specificity: number of true negative decisions/number of actually negative cases.
- Total classification accuracy: number of correct decisions/total number of cases [36].

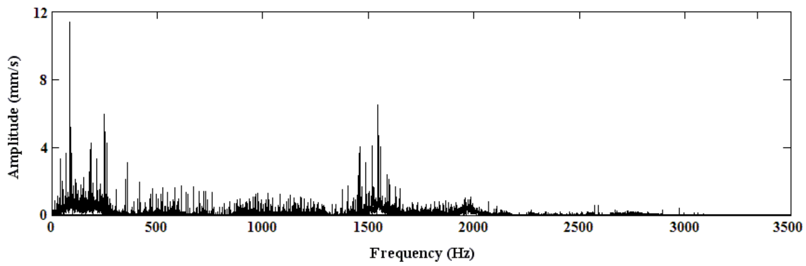

Fig. 6. Frequency spectrum of defective journal bearing

In order to confirm the robustness of the proposed classification procedure, the authors compared the classification results between the SVM and two common classifiers, namely, FLD and KNN. The entire analysis was implemented by using the Matlab R2008a software package. For the classifiers, the target values were specified as 1 and -1, respectively, representing normal and faulty conditions. After training stage, testing dataset were used to validate the accuracy of three classifiers for the identification and classification of the journal bearing conditions. Results are presented to see the effects of signal processing, feature extraction for diagnosis of journal bearing condition using FLD, KNN and SVM.

Simulation Results

The classical and QP solution were performed for the FLD analysis and linear classification was used for classifying the test dataset. The variable K values were selected in the range of 1 to 10 with a step size of 1, also the Euclidean distance and nearest rule (Majority rule with nearest point tie-break) were used for the KNN. The performance of a SVM depends on the choice of the kernel function to map a data from original space to a higher dimensional feature space. There are no certain rules governing its choice. The RBF kernel is the one of the best kernel for constructing SVM and provides excellent results for fault diagnosis applications [37]. The penalty parameter of 10^3 (C), the Quadratic Programming method with condition parameter of 10^{-7} and the RBF kernel with the variable value of the kernel width in the range of 0.1 to 1 with a step size of 0.1 were used for the SVM.

Tables 1, 2 and 3 list the classification results of each classifier under their variable parameter.

Table 1. Performance of Fisher Linear Discriminant

Solution method	Train success (%)	Test success (%)	Time (s)
Classic	88.46	71.43	0.0015
QP	92.31	85.71	0.015

Performance Comparison of FLD, KNN and SVM

The performance of the QP solution was better than the classical solution for the FLD, but its computation time was 0.015 which was much higher than the classical solution. The results indicate that the performance of FLD is relatively acceptable. The KNN is a classifier that its accuracy is always 100 % on training dataset, because the KNN holds position of training data and their class during the classification process. By examining Table 2 it can be observed that the best accuracy was 78.58 %, which belonged to $K = 6$ and $K = 10$, but the performance of the KNN was better for $K = 10$, because its computation time was relatively lower than for $K = 6$. Fig. 7 illustrates the difference of the accuracy rate for the different values of K. High-dimensional feature space confused the KNN classifier and therefore causes the classification success to reduce clearly. This confirms that a proper feature selection method is needed for FLD and KNN classifiers, which remove the redundant features from the original feature set such as improved distance evaluation technique [38]. It should be emphasized that a drastic reduction of features can lead to a decrease in the accuracy rate [37].

Table 2. Performance of K-Nearest Neighbor

K	Performance (%)	Time (s)
1	71.43	0.0058
2	71.43	0.0039
3	71.43	0.0033
4	64.29	0.0036
5	71.43	0.0033
6	78.58	0.0041
7	71.43	0.0033
8	50	0.0037
9	64.29	0.0032
10	78.58	0.0035

Table 3. Performance of Support Vector Machine

RBF kernel width (σ)	Train Success (%)	Test Success (%)	Time (s)
0.1	100	100	0.038
0.2	100	100	0.041
0.3	100	100	0.042
0.4	100	100	0.04
0.5	100	100	0.04
0.6	100	100	0.069
0.7	100	100	0.039
0.8	100	100	0.059
0.9	100	100	0.047
1	100	100	0.04

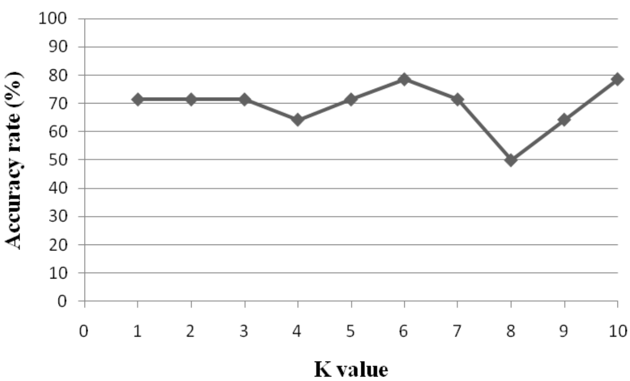

Fig. 7. Performance of KNN for variable K value

The performance of the SVM was 100 % for all values of RBF kernel width (σ). The difference was only in the time of computing. The performance of the SVM was relatively better for the RBF kernel width (σ) of 0.1, due to the lower computation time. The RBF kernel width (σ) of 0.6 performed the classification longest. The difference of the computation time for the various value of σ is given in Fig. 8. The performance of the SVM was substantially better than the FLD and KNN. The results imply that the SVMs combination can successfully identify various machine conditions. All the above results prove that it would be better to combine signal processing and feature extraction techniques with SVM classifier than to use FLD and KNN classifiers. The proposed diagnostic method have gained significant achievements in detection accuracy and provided a better generalization capability compared to the traditional classifiers.

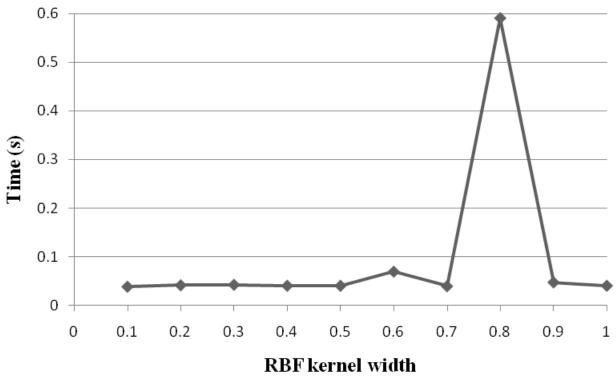

Fig. 8. Effect of RBF kernel width (σ) on computation time for SVM

Conclusions

The applications of the procedure presented in this work are intended to be an analysis tool that can be applied in the incipient detection problem of engine main journal bearing faults. The presence of a defect in the main journal bearing was investigated by the frequency spectrum analysis. 30 features were extracted from the frequency domain signals such as Maximum, Minimum, Average, Standard Deviation (Stdv), Variance (Var), 4th central moment, 5th central moment, Skewness, Kurtosis, etc. Finally, Fisher Linear Discriminant (FLD), K-Nearest Neighbor (KNN) and Support Vector Machine (SVM) were applied to classify the conditions of the journal bearing. The experimental results demonstrated whether the main journal bearing of engine is intact or defective. The output from classifiers, especially SVM, can be used for online condition monitoring. Also, the results indicate that the use of the statistical and vibration parameters to extract appropriate features from vibration signals is necessary for better diagnostic model performance. The classification results have been presented in Tables 1, 2 and 3. It was observed that the features extracted directly have affected the classification results. Also, there are considerable variations in the accuracy rate of the classifiers. The performance of the SVM has been found to be significantly better in comparison to the FLD and KNN with the entire dataset. This is due to its unique ability in classification and generalization. The computation time was generally less for the KNN than for the FLD and SVM. The results demonstrate the ability and reliability of the proposed method in the fault diagnosis of the main journal bearing of the internal combustion engine.

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