Machinery Bearing Fault Diagnosis Using Variational Mode Decomposition and Support Vector Machine as a Classifier

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Abstract. Crack propagation is a major cause of failure in rotating machines. It adversely affects the productivity, safety, and the machining quality. Hence, detecting the crack’s severity accurately is imperative for the predictive maintenance of such machines. Fault diagnosis is an established concept in identifying the faults, for observing the non-linear behaviour of the vibration signals at various operating conditions. In this work, we find the classification efficiencies for both original and the reconstructed vibrational signals. The reconstructed signals are obtained using Variational Mode Decomposition (VMD), by splitting the original signal into three intrinsic mode functional components and framing them accordingly. Feature extraction, feature selection and feature classification are the three phases in obtaining the classification efficiencies. All the statistical features from the original signals and reconstructed signals are found out in feature extraction process individually. A few statistical parameters are selected in feature selection process and are classified using the SVM classifier. The obtained results show the best parameters and appropriate kernel in SVM classifier for detecting the faults in bearings. Hence, we conclude that better results were obtained by VMD and SVM process over normal process using SVM. This is owing to denoising and filtering the raw vibrational signals.

Keywords: Variational Mode Decomposition (VMD), Intrinsic Mode Functions (IMF), Support Vector Machine (SVM), Crack propagation.

1. Introduction

Bearings are the vital components for smooth machining operations. The priority for examining the faults in bearing is a predominant task. Cracks, corrosion and heat are some common causes for faults to originate. Either the visual inspection or the noises from the machines are common techniques to observe faults in the bearings. But life of the bearings cannot be determined by these techniques. To know the severity of failure it is preferred to quantify the probability of fault. The fault diagnosis is a significant process in condition based maintenance that involves two steps, data acquisition and its technical interpretation. The fault can be diagnosed by continuously or periodically recording the variables for further processing, analysing and then interpreting the results. Variational mode decomposition (VMD), Empirical mode decomposition (EMD), Empirical wavelet transform (EWT)

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etc. are some of the fault diagnosis techniques used in industries for fault detection. [1] - [2]. These concepts have many applications in the field of automobile industries, aerospace, manufacturing industries, power quality signals etc.

2. Variational Mode Decomposition
Variational mode decomposition is an advance fault diagnosis technique used in automobile industries to detect the faults in rotating components like bearings, shafts, gears etc. Generally, this method decomposes a signal into corresponding IMF components, using the mathematical procedure - calculus of variation. An individual mode of a signal is estimated to have a closed frequency which is varied with respect to central frequency (severity). The main aim of VMD is to reconstruct the original signal by modulating the intrinsic mode function components (IMF) [1]. The modulation is done on the input using an optimization method called ADMM (Alternative Direction Method of Multipliers). This should be done in such a way that the reconstructed signal pattern should be similar to the original signal [2]. It helps in analysing the behaviour of bearing faults and also denoises the external disturbances caused during the machining operation. The advantage of VMD is that, we can assign the number of modes based on raw data, when compared to empirical mode decomposition. Figure 1 gives a detailed procedure of the sequence of steps followed in VMD methodology.

![Flow Chart of VMD Process](image)

**Figure 1.** Flow Chart of VMD Process
3. Fault Simulator Machine
Fault simulator machine shown in figure 2, is used to generate the vibrational signals of rotating components and captures the signals using a PCB accelerometer which is connected to a DAQ system shown in figure 3. The bearing status is monitored for three different essential cases. The foremost experiment is done for a flawless ball bearing, whose data is standardized for evaluation. The subsequent experiments are for the defects in inner race bearing and for the defects in outer race bearing. We have used the “National instruments”, DAQ system of model number DAQ - 9174 with the specifications of sampling frequency of 25600Hz, sensitivity around 99.1 mv/gm.

4. Fast Fourier Transform (FFT)
FFT is a mathematical algorithm for converting the time domain functions into frequency domain functions. It is a complicated algorithm which speeds up the signal analysis process such as filter simulation and power spectrum analysis by means of digital computers. The frequency values helps in analysing the vibration signal to identify the peak values. The fault conditions can be estimated within the given frequency range before the damage cascades to effect the other components in the machine.

5. Support Vector Machine (SVM)
SVM is a supervised classification tool which is developed from statistical learning theory. It uses a kernel function to analyse the training and testing data. The idea is to minimize the generalization error by increasing the maximum marginal distance between the two data sets by creating a hyper-plane. [4] - [7]. The linear separation of a two class problem is explained in figure 4 by using a straight line.
Let us examine a set of classes where $x_1$ and $x_2$ are two variables. The main aim of SVM is to create a hyper-plane in the form of \( c_1 x_1 + c_2 x_2 - \gamma = 0 \) with the bounding planes \( c_1 x_1 + c_2 x_2 - \gamma \geq 1 \). Here \( \gamma \) is a scalar term. In the initial stage (training), SVM finds the corresponding \( c_1 \) and \( \gamma \) terms. If these factors are identified, the decision boundary is obtained as \( x - \gamma = 0 \), where \( c \) is a vector term. When a new data point is determined, we can label the decision using a function \( f(x) = \text{sign}(x - \gamma) \).

This basic idea of SVM helps in analysing the data for finding out the classification efficiencies.

6. Proposed Methodology

Three different fault bearing cases were considered for finding out the classification accuracies using the vibration signals which are generated during the machining operations. Obtained signals are observed clearly using the Lab –View software and were stored in a computer through data acquisition system. Following were the three bearing conditions where the fault simulator machine was operated at the rpm’s of 400, 500, 600, 700, and 800.

- Good Bearing
- Fault in the Inner race bearing
- Fault in the Outer race bearing

For each rpm, 150 samples were collected at a sampled rate of 25,600 Hz. High frequency range helps in analysing the signal pattern easily and also to observe the faults clearly. The time domain vibrational signals were decomposed into a set of IMF components using VMD. These high frequency signals help in obtaining a good classification accuracy value. Using these IMF components, we reconstruct the signal in such a way that it should be similar to the original signal. All the statistical parameters were extracted from the reconstructed signal and the original signals for the bearing faults, and were fed into the SVM classifier. This data is used in feature selection and feature classification process for training and testing the classifier. Finally an appropriate classification accuracy value is found out for the bearing faults using this methodology. Obtained results show that the classification efficiency value obtained using VMD is better than the classification efficiency obtained using original signal.

7. Results and Discussions

In this work, VMD process is applied for three bearing conditions which are shown in table 1. Based on few input specifications, the classification accuracy values vary for different classification tools.
After thorough observation and analysis, we have fixed a few tuning parametric values in the SVM classifier for analysing the features of bearing faults. Extremely low values of $\alpha$ do not make sense, since the original signal and the reconstructed signal will be exact. Higher values of “$\alpha$” show a little improvement in the signal pattern, but when the values are further increased, we observe an increase in the band width thickness. Hence, “$\alpha$”, which is the balancing data fidelity parameter, is set to an optimum value of 100. Thus, observations by trial and experiment help fix the input parameter values; such that the reconstructed signal is almost similar to the original signal.

The sample data-plots of three different ball bearing conditions are shown in figure 5, figure 6, and figure 7, which are obtained by reconstructing the original signal by using the VMD process.

7.1. Good Bearing
The VMD algorithm is implemented to the good bearing and is reconstructed in the following manner. This graph figure 5 represents the time-domain signal, which exemplifies the amplitude varying with respect to time. Here the original signal is generated during the machining operation with external disturbances, is de-noised and then reconstructed using the VMD process.

![Figure 5](image_url)

**Figure 5. Vibrational Signal for Good Bearing**

7.2. Inner Race Fault bearing
This graph in figure 6 represents the time-domain signal, which expresses the amplitude varying with respect to time. By using the VMD process we de-noise and reconstruct the signal which is shown below.
7.3. Fault in Outer Race Bearing

Figure 7 represents the faults in outer race bearing using VMD process.

**Figure 6.** Vibrational signal for inner race fault bearing

**Figure 7.** Vibrational signal for the fault in outer race bearing
Table 1. Original signals using different kernels in SVM

| Testing parameters          | Polynomial Kernel | PUK Kernel | RBF Kernel | Mean   |
|-----------------------------|-------------------|------------|------------|--------|
| Time (sec)                  | 0.63              | 4.52       | 0.33       | 1.826  |
| Total instances             | 2250              | 2250       | 2250       | 2250   |
| Correctly classified        | 1775              | 1914       | 2109       | 1933   |
| Incorrectly classified      | 475               | 336        | 141        | 317    |
| Classification efficiency % | 78.89             | 85.067     | 73.067     | 79.008 |

The above table shows that the Pearson VII based universal kernel (PUK) gave us the maximum classification accuracy percentage of 85.067%, hence, it is chosen as the best kernel function in SVM classifier. The mean classification accuracy gives us the maximum efficiency in determining the faults. Here, the entire data of the original signal using SVM classifier is analysed but the denoising is not done where we have some fault information. Hence, we need to de-noise the signal using VMD process. The following table 2 uses the reconstructed signal statistical features which were analysed using SVM classifier.

Table 2. Reconstructed Signals using different kernels in SVM

| Testing parameters          | Polynomial Kernel | PUK Kernel | RBF Kernel | Mean   |
|-----------------------------|-------------------|------------|------------|--------|
| Time (sec)                  | 0.33              | 2.52       | 11.92      | 4.92   |
| Total instances             | 2250              | 2250       | 2250       | 2250   |
| Correctly classified        | 2109              | 2234       | 1809       | 2051   |
| Incorrectly classified      | 141               | 16         | 445        | 201    |
| Classification efficiency % | 93.733            | 99.2889    | 80.22      | 91.08  |

The maximum efficiency value depends on choosing the appropriate kernel function and the parameters. The PUK kernel in SVM classifier gives the maximum efficiency value. The reconstructed signal gives us greater efficiency when compared to the original signals. A 3*3 confusion matrix is obtained in which the elements in diagonal are classified properly and the other elements are not classified properly. From the obtained confusion matrix, we can conclude that VMD process outpaces well. Table 3 and Table 4 show the confusion matrix for both the original signal and the reconstructed signals using PUK kernel.

Table 3

| Confusion Matrix | a     | b     | c     |
|------------------|-------|-------|-------|
| a                | 735   | 15    | 0     |
| b                | 30    | 587   | 153   |
| c                | 1     | 137   | 612   |
Table 4

| Confusion Matrix | a   | b   | c   |
|------------------|-----|-----|-----|
| a                | 749 | 1   | 0   |
| b                | 0   | 742 | 8   |
| c                | 0   | 137 | 743 |

Here the data is classified as:
- a = good bearing,
- b = Fault in inner race bearing,
- c = Fault in outer race bearing.

Thus, the original signal gives a classification accuracy percentage of around 85.0667% and the reconstructed signal gives 99.2889%. This information helps us in analysing the faults in order to predict the defects in the bearing components accurately. Hence, we opted for the VMD process in identifying the faults and obtained a good classification accuracy value. The accompanying figures that are from figure 8 to figure 13 gives the exact information about faults in the bearings and best kernel in SVM tool which are applied individually, at each RPM, for both the signals. The notations in graphs indicate the following:

- Org - cc and org - ic = original signal instances which are classified correctly and incorrectly.
- Rec - cc and rec - ic = reconstructed signal instances which are classified correctly and incorrectly.
- Efficiencies 1 and 2 indicate both original and reconstructed signal classification efficiencies.
- Time 1 and 2 indicates the corresponding times at those conditions.

**Figure 8.** Classified and Incorrectly Classified Data

**Figure 9.** Efficiencies and Time v/s RPMs
Fault diagnosis of bearing components in rotating machine is done using VMD algorithm, by taking the vibration signals as an input. Feature extraction, feature selection and feature classification were the three phases of machine learning techniques. Here SVM is used as a classification tool by considering a few statistical features in feature selection phase. The classification efficiency obtained using VMD yields 99.2889% accurate results when compared with classification efficiency of original signal, which gave 85.0669%. Here there is a difference of 14.22% error in identifying the faults in a component. So from this error of 14.22 %, we can conclude that implementation of VMD process using SVM classifier produces a better result in identifying the faults. A few parametric values for the analysis were fixed which helps to find out the fault behaviors in real time applications as well. Hence, PUK is chosen as the best kernel among the three kernel functions in SVM classifier, since it gives the
maximum classification efficiencies for all the rpms. The selection of the best kernel depends on the following factors. They are:

- Selection of statistical features
- Number of features to be selected
- Computational time for the analysis,
- Classification efficiencies
- Correctly classified instances
- Error percentages and Vibration signal patterns.

Hence, from the above analysis we can conclude that reconstructed signals generated by VMD outpaces well than the results obtained using original signals. Thus, this information is enough to diagnose the faults in bearings accurately.

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