Research on intelligent fault diagnosis of gears using EMD, spectral features and data mining techniques

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Abstract: In this present work aims to formulate an automated prediction model using vibration signals of various gear operating conditions by using EMD (empirical mode decomposition) and spectral features and different classification algorithms. In this present work empirical mode decomposition (EMD) is a signal processing technique used to extract more useful fault information from the vibration signals. The proposed method described in following parts gear test rig, data acquisition system, signal processing, feature extraction and classification algorithms and finally identification. Meanwhile, in order to remove the redundant and irrelevant spectral features and classification algorithms, data mining is implemented and it showed promising prediction results.

1. Introduction

Gear is one of the vital components used in rotating machinery for power transmission. The condition under which the gear operates adversely affects the performance of rotating machine. Fault in a gear is an unavoidable part and may result in abnormal behavior and often failure in the system. It is therefore necessary to detect the faults in gear and diagnose at early stages. Vibration analysis is one of the fault diagnosis methods, which is widely used because of simplicity in measurement. All the critical information in terms of faults can be obtained using vibration signal processing techniques. In diagnostics, signal processing technique is widely used to characterize the state of the system. Since the last decade several types of signal processing techniques have been developed. The results obtained from different types of signal processing techniques are often different from each other. Therefore, suitable techniques are selected for a specific system or component, depending upon the environmental conditions. Empirical mode decomposition (EMD) [1, 2] is a signal processing method in which complicated data signals which are most often non-stationary or non-linear can be decomposed into intrinsic mode function (IMF) in finite set. These intrinsic mode functions are used to find the solution for Hilbert-Huang Transform [3]. Cheng et al. [4] proposed the concept of local Hilbert energy spectrum. Two gear fault diagnosis techniques were applied which included frequency family separation technique and local Hilbert energy spectrum technique to diagnose the gear with fault. Support vector machines (SVM) [5-7] are used in combination with IMF auto regressive models to identify the working condition of gear. Feature extraction of vibration signals of gear was done with the help of EMD. Faulty vibration signals of gear were extracted using the AR model. SVM was used to obtain the fault recognition pattern. Michael Feldman [8] explained how under the influence of harmonic functions the corresponding operational behavior of EMD changes. EMD technique is widely used in combination with other signal processing techniques such wavelet transform [9], Fourier transform and other such techniques for better
outcome. Lin and Hongbing [10] studied a new method for feature extraction of signals in which standard EMD method and the inverse EMD filters are combined to obtain a better decomposition technique of multicomponent signals. They proposed that inverse EMD filter has better performance for signals having lower frequency. Median filter is another processing method which can be combined with EMD to analyze friction signals [11]. Median filter is process is used to reduce random noise in the signals. Most often, unwanted noise is produced by the measuring system which can be removed using median filter. Amaranth and Praveen Krishna [12, 13, 17] investigated the surface wear failure in spur as well as helical gears using EMD technique. Ensemble empirical mode decomposition (EEMD) technique is used to extract feature related to faults for the vibration signals. In case of helical gear, EMD is applied to vibration and acoustic signals and based on the kurtosis value, for both the input signals and empirical mode decomposition obtained the upper hand of EMD is exhibited. Kedadouche et al [14] applied combination of EMD and Lempel-Ziv complexity method the detect damage in an early stage of gear. Hassan and Bhuiyan [15] demonstrated the effectiveness of sleep scoring algorithm combine with TQWT features. Mcfadden and Smith [16] explained how the defect influencing the dynamic characteristic of the rolling bear with radial load.

2. Process methodology:
In this study, EMD as a signal processing tool is used to find the intrinsic mode functions for the gear data obtained through experiments. The fault information acquired through EMD are then extracted and categorized into different spectral features [14]. Spectral features provide input to the data mining procedure which classifies the data through classification algorithm. This classified data is extensively compared to predict the health condition of gear. Figure1 depicts the process methodology presented in this paper and steps involved to diagnose the condition of the gear.

![Figure 1. Process methodology](image)

3. Experimental setup:
To study the wear of gear under accelerated test condition, the experiment setup was accordingly arranged. A gear test rig was used in this experiment. Two parallel shafts and four gears along with pinion and gear pairs were used in the arrangement. Gear box was parallel arranged in the system. A variable frequency drive (VFD) was used for controlling the speeds, three face 10HP induction motor and break drum dynamometer were connected to the gear box to control the loads, Tri axial accelerometer used to measure the vibration signals. For collecting the vibration data 24bit signal processor dewesoft analyzer and computer with data acquisition software were used. Rotating speed of the gear set was maintained constantly. Steady load was applied by brake drum dynamometer and the speed monitor by tachometer. And the fault size is maintained for all three components.
For this experimental setup, the arrangement, the designing complexity of the driving system was significantly reduced. This approach of testing and investigating the gear system was all the more reliable. The gearbox used in the experimental setup was operated at 1700 rpm under accelerated test conditions. Vibration signals were captured by a tri-axial type accelerometer. A 24 bit data acquisition system which almost collects 5000 data points per second was used to capture the signals.

4. Theoretical background of EMD

Empirical mode decomposition method was derived and acknowledged by Huang as the fundamental part of Hilbert-Huang Transform (HHT) and he applied this time-space analysis method for the processing non-stationary as well as non-linear vibration signals. Without actually departing from time domain, the signal processing method is used to convert multi-component vibration signals into number of mono-component signals called as intrinsic mode functions (IMF) as they are called, using the EMD algorithm. An IMF is a function in the family of frequency that must satisfy the following two conditions: (1) in the entire set of data, the number of extreme and the number of zero-crossings must either equal or differ at most by one, and (2) at any point, the local average is zero, meaning the mean value of the upper envelope of data set (local maxima) and lower envelope of data set (local minima) is zero. This technique is all the more useful in analyzing the natural non-stationary signals. Table below depicts the process steps involved in EMD method considering a signal x(t) and the figure depicts the pictorial representation of this particular signal processing technique.

Table 1. Algorithm used for EMD

| Step | Description |
|------|-------------|
| 1)   | Initialize: \( r_0 = x(t) \) and \( i=1 \) |
| 2)   | Extract the \( i^{th} \) IMF \( c_i \) |
| a.   | Initialize: \( h_{0(k,1)} = r_{i-1}, k=1 \) |
| b.   | Extract the local maxima and minima of \( h_{0(k,1)} \) |
| c.   | Interpolate the local maxima and minima by cubic spline lines from upper and lower envelopes of \( h_{0(k,1)} \) |
| d.   | Calculate the mean \( m_{0(k,1)} \) of the upper and lower envelopes of \( h_{0(k,1)} \) |
| e.   | Let \( h_k = h_{0(k,1)} - m_{0(k,1)} \) |
| f.   | If \( h_k \) is an IMF then set \( c_i = h_k \), else go to step (b) with \( k=k+1 \) |
| 3)   | Define the remainder \( r_{i+1} = r_{i} - c_i \) |
| 4)   | If \( r_{i+1} \) still has least 2 extrema then go to step(2) within=\( i+1 \) else the decomposition process is finished and \( r_{i+1} \) is the residue of the signal. |

In the concluding part of the procedure a residue \( r_I \) is obtained and set of \( I \) IMFs \( c_i \) \((i = 1, 2, \ldots, I)\). Taking the summation of all IMFs and the final residue \( r_I \) we get, \( x(t) = \sum_{i=1}^{I} c_i + r_I \). Hence, it is possible to decompose a signal into \( I \) IMFs and a residue \( r_I \) which is the mean trend of \( x(t) \). The
IMFs, \( c_1, c_2, \ldots, c_i \) include different frequency bands ranging from high to low. The frequency components contained in each frequency band are different and they change with the variation of the signal \( x(t) \), while \( r_i \) represents the central tendency of the signal \( x(t) \).

**Figure 3.** EMD method employed for signal processing

### 5. Spectral Features:

Spectral features are the features based on frequency domain used in audio and speech signal classification which are obtained by converting the time based signal into the frequency domain using the Fourier Transform, like: fundamental frequency, spectral slope, spectral decrease, spectral density, spectral roll-off, etc. These features can be used to identify the notes, pitch, rhythm, and melody of a given input signal. In this paper, application of spectral spread, spectral flatness, spectral slope, spectral decrease, and spectral roll-off are applied. A brief discussion is given in the below.

**5.1 Spectral spread**

Spectral spread can also be called as instantaneous bandwidth. The concentration of the magnitude spectrum around the spectral centroid can be shown by using spectral spread. It can be also said as standard deviation of magnitude spectrum around the spectral centroid. It is expressed by

\[
SS = \sum_{q=0}^{M-1} \frac{(q - SC)^2}{\sum_{q=0}^{M-1} |Y(q)|}
\]

**5.2 Spectral slope**

Spectral slope evaluates the spectral shape by using an approximation of the magnitude spectrum technique. Linear regression is applied to find the approximation of the magnitude spectrum. Modeling a linear function from the magnitude spectrum of the faulty gear signal, spectral slope is calculated by using the mathematical expression as follows.

\[
SSl = \frac{M \sum_{q=0}^{M-1} F_n |Y(q)| - \sum_{q=0}^{M-1} |Y(q)|}{M \sum_{q=0}^{M-1} F_n^2 - \left( \sum_{q=0}^{M-1} |Y(q)| \right)^2}
\]
5.3 Spectral roll-off

Spectral roll-off is nth percentile of spectral distribution of the signal. n ranges from 80% to 90% it is the frequency below which the nth percentile of the magnitude distribution is concentrated. Spectral roll-off computes the spectral energy concentration of the given input signal. It is expressed as

\[ SR = \frac{1}{100} \sum_{q=0}^{n} |Y(q)| = \frac{C}{100} \sum_{q=0}^{M-1} |Y(q)| \]  

6. Classification algorithms:

6.1 Classification through IBK

Sets whether the mean squared error is utilized instead of mean absolute error while doing cross-validation. Sets the most extreme number of cases permitted in the preparation pool. IBK classifier. Simple instances occurrence based learner that uses the class of the closest k preparing cases for the class of the test cases.

6.2 Classification through K-star

K-STAR classifier is a variant of p Lazy algorithms. K-Star uses an entropy measure to transform a sample p to another, by randomly choosing k between possible g transformations. Given a set of samples s and a set of possible u transformations T, it will map s: S→S, that is, k is a sample (a) to another sample (b). Then p T* consists of members that have unique h mapping on S, given by

\[ (a) = (s_{n-1}(…s_1(a)…)) \]  

where s=s1,…sn, the probability function on T* is given by p. P* is defined as the probability of all possible paths between sample (a) and sample (b) and is given by

\[ P* \times (ba) = \sum_{s \in T \times s(a)} P(s) = b \]  

And hence the K* function is given as

\[ K* \times (ba) = -\log_2 P* (ba) \]  

6.3 Classification through J48

J48 classifier is a straightforward C4.5 decision tree for classification. It makes a binary tree. The decision tree approach is most helpful in classification issue. With this procedure, a tree is developed to show the classification process. Once the tree is assembled, it is connected to each tuple in the database and brings about classification for that tuple. J48 permits classification. Through either decision trees or rules created from them.
7. Results and discussions
To demonstrate the effectiveness of the proposed diagnosis method for the gear faults, the vibration data acquired from the gear setup are used. Vibration signals have been decomposed into different frequencies i.e. IMF1, IMF2, IMF3, IMF4, IMF5 using EMD method. Time domain and corresponding frequency spectrum of different fault conditions are given in Figure 4.

Figure 4 (a). Time waveform of Gear 0Hr
Figure 4 (b). Frequency spectrum of Gear 0Hr
Figure 4 (c). Time waveform of Gear 36Hr
Figure 4 (d). Frequency spectrum of Gear 36Hr
Figure 4 (e). Time waveform of Gear 72Hr

Figure 4 (f). Frequency spectrum of Gear 72Hr

Figure 4 (g). Time waveform of Gear 108Hr

Figure 4 (h). Frequency spectrum of Gear 108Hr
Figure 4 (i). Time wave form of Gear 144Hr

Figure 4 (j). Frequency spectrum of Gear 144Hr

The figures above represent the different spectrum of gear condition. In the corresponding frequency range of every IMFs say mode 1(frequency range of IMF1) contains the most signal frequencies, mode 2 the following higher signal frequencies. With the assistance of this information, the informative features in this automated fault diagnosis analysis approach, which are gathered from the gear fault frequencies, will give more prediction accuracy.

The selection of IMFS is based on following criteria. From the frequency spectrum for 0 hour data set of IMF 1 is centered from 2000Hz to 4000Hz, in second IMF frequency spectrum is centered from 1000Hz to 4000Hz. In IMF3 it is centered from 500Hz to 2000Hz. In IMF4 frequency spectrum is centered from 200Hz to 1000Hz. In second condition, that is for 36 hours data set of gear the IMF2 and IMF3 is centered from 1500Hz to 2500Hz. which can be associated with the characteristic bearing frequency of the component. Similarly in Fig6 (f) and Fig6 (h) the IMF2 and IMF3 is centered from same range. IMFs in both frequency and time domain are clearer even if it is hard to find fault characteristics which can distinguish the all conditions. All the spectral features based features are normalized before given as input to the feature selection and classification algorithms.

In this present work feature selection process is done by working out with different classifiers. The feature selection processes were done in MATLAB. The input features are two types: Time and frequency domain features that are extracted from time and frequency IMFs of EMD and selected features from the same are separately fed input into WEKA classifiers such BayesNet, DMNBtext, Logistic, RBFnetwork, K-star, IBK, AttributeSelectedClassifier, Dagging, Hyperpipes, VFI, DTNB, JRIP, J48, LADTREE to find out the different states of gear. WEKA is open source software used for the data mining technique or in other words used to create classification algorithms.

The simulation results are shown in Table 2. and Table 3. Table 2 summarizes the result based on accuracy, time taken and kappa statistics for each simulation. Table.3 shows results based on errors. Figure 5 and figure 6 represent the graphical representation of simulation results. It can be clearly noticed that highest accuracy obtained is 99.5067% which belongs to the K-Star classification and lowest is 32.9561 % it belongs to Dagging classifier. It is noticed that IBK classification requires shortest time 0.26 seconds compare to the other classifications.
Table 2. Results of the classification algorithms with respect to accuracy category

| Classifier | Classification | Correctly classified instances in % | Incorrectly classified instances in % | Kappa statistics | Run time |
|------------|----------------|-------------------------------------|---------------------------------------|------------------|----------|
| Bayes      | BayesNet       | 56.3542                             | 43.6458                               | 0.45             | 0.33     |
| Functions  | Logistics      | 98.2387                             | 1.7613                                | 0.95             | 0.32     |
| Lazy       | IBK            | 98.1572                             | 1.8428                                | 0.95             | 0.26     |
| Meta       | AttributeSelectedClassifier | 80.3728                           | 19.6272                               | 0.75             | 0.27     |
| Misc       | Dagging        | 32.9561                             | 67.0439                               | 0.15             | 0.53     |
| Rules      | DTNB           | 56.1521                             | 43.8479                               | 0.45             | 0.35     |
| Trees      | J48            | 84.9811                             | 15.0189                               | 0.8              | 0.28     |
|            | LADTree        | 56.6511                             | 43.3489                               | 0.45             | 0.27     |

Table 3. Results of the classification algorithms with respect to error category

| Classifier | Classifications | Mean absolute Error | Root squared error | Relative Absolute error in % | Root relative squared error in (%) |
|------------|-----------------|---------------------|--------------------|-----------------------------|-----------------------------------|
| Bayes      | BayesNet        | 0.238               | 0.3301             | 74.3653                     | 82.5301                           |
| Functions  | Logistics       | 0.1251              | 0.1465             | 14.656                      | 13.325                            |
| Lazy       | IBK             | 0.1336              | 0.1767             | 16.667                      | 16.667                            |
| Meta       | AttributeSelectedClassifier | 0.1044              | 0.2285             | 32.619                      | 57.1131                           |
| Misc       | Dagging         | 0.3121              | 0.3929             | 97.5238                     | 98.2202                           |
| Rules      | DTNB            | 0.2557              | 0.3393             | 79.8992                     | 84.8335                           |
| Trees      | J48             | 0.0907              | 0.2129             | 28.3333                     | 53.2291                           |
|            | LADTree         | 0.1909              | 0.3546             | 59.652                      | 88.6501                           |

Kappa statistics is utilized to evaluate the accuracy. It is normal to recognize the reliability of the data collected and their validity. Kappa > 0.75 as excellent, 0.40-0.75 as fair to good, and < 0.40 as poor. In this work, the kappa score for selected algorithms is around 0.11 to 0.99. K-star classification gives good status kappa value 0.98 and lead the list of the results.

In this present work normally utilized indicators, for example, mean absolute error and relative
absolute errors that belong to regression absolute measure were implied and relative absolute error and root mean square error is derived from regression absolute measure and regression mean measure component. Lower error indicates that it has more powerful classification capability. It is observed that the lowest error is found in J48 network classifier in the entire of all sets of classification.

![Figure5](image)

**Figure5.** Comparison between different evaluation parameters of different classifications

![Figure6](image)

**Figure6.** Comparison of different classifications under accuracy category

8. Conclusion

In this proposed work, therealt ime experimental vibration data sets are collected and used to evaluate the performance in fault diagnosis of gears. EMD is used to extract characteristics from the non-stationary signal. Spectra features derived from IMFs of EMD on both time and frequency domain vibration signals of various faultless and faulty conditions of gear are used in this methodology. Meanwhile, in order to remove the redundant and irrelevant features and classification algorithms, data mining is implemented and it showed promising prediction results. The final comparison results indicate the effect of feature extraction based on EMD and different classification algorithms. Altogether, EMD IMFs extracted spectral features optimized by different classification process, and in contrast, K-star network classification gives better results with respect to accuracy category with accuracy of 99.5067% compared to other classifications in the same condition in gear fault diagnosis while J48 gives better results with respect to error category with absolute mean error of 0.0907 which is the least among all the other classifications.
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