Fault Diagnosis of Ball Bearing Using Hilbert Huang Transform and LASSO Feature Ranking Technique

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Abstract. Bearings are one of the crucial components of any machine having rotary parts. They are employed to support and ensure smooth operations of the shafts in the rotary machinery. Therefore, any fault in the bearings can lead to a decline in the level of production and equipment. For this reason, it is important to monitor the bearing health. This paper presents a signal analysis technique for machine health monitoring using the Hilbert-Huang Transform (HHT). HHT is a time domain approach which extracts instantaneous frequency data from a signal by decomposing the signal into Intrinsic Mode Functions (IMF) using the Empirical Mode Decomposition (EMD). The Least Absolute Shrinkage and Selection Operator (LASSO) is used as feature ranking method which is used to improve the prediction accuracy by reducing input data to machine learning model by aiding to select only a subset of the feature vector rather than using all of the features. In the present work, training and tenfold cross-validation accuracy or two classifiers have been compared. The comparative analysis presented in this paper reveals that the utilization of LASSO as a feature ranking method shows a substantial decrease in the data to be handled and improving the diagnosis accuracy.

Keywords: Fault Diagnosis, HHT, LASSO, Machine Learning

1. Introduction
Bearing failures can be simplified into generally recognized categories: bearing fatigue, bearing seizure, bearing corrosion, contamination, improper lubrication, and so on. In the case of bearings, abnormal vibrations can be detected when the rolling elements interact with the surface of the defect and due to the intrinsic characteristics of each fault type, the frequency of the abnormal vibrations occurring are different depending on the type of fault [1]. Several techniques for detection of faults in rolling element bearing exist today. The vibration-based signal processing method is among one of the popular methods for diagnosing bearing faults. Fourier Transforms have been extensively used as a signal analysis tool for fault detection in bearings. However, the Fourier Transform is best suited for stationary signals i.e. signals having time-invariant properties [2]. The vibration signals that researchers encounter in faulty rolling element bearings are mainly non-stationary with a split second between changes in the amplitude of vibration signal which makes it difficult to quantify. Hence, it is
crucial to detect these non-stationary signals effectively in order to prevent imminent machine failures. Wavelet Transform (WT) is an alternative approach to analyze non-stationary signals by utilizing the change in energy distribution with respect to time along with each frequency band [3]. One of the major drawbacks of the wavelet transform is the selection of base function for mother wavelet. In addition, WT faces a problem of energy leakage due to the limitation of the length of the wavelet function. To tackle these drawbacks of the WT, researchers have used the Hilbert-Huang Transform (HHT). HHT employs an adaptive time-frequency analysis which eliminates the requirement of prior functional basis [4]. Rather, HHT adaptively derives the basic functions from the data by utilizing Empirical Mode Decomposition (EMD). The derived basic functions obtain after performing on the original signals gives Intrinsic Mode Functions (IMF). A phenomenon known as Mode aliasing is observed in EMD and to overcome Ensemble Empirical Mode Decompositions (EEMD) was derived. Feature selection also known as feature ranking is gaining attraction nowadays. Feature ranking is a technique to select relevant features to avoid the curse of dimensionality as well to enhance the generalization capability of classifier used. In feature ranking technique the accuracy of machine learning model is evaluated using the ranked feature set [5-6]. The use of LASSO as a feature ranking and selection method provides benefits over the previous approaches in terms of the amount of data that needs to be handled when classifying the bearing faults. In order to rank the features, LASSO utilizes the linear dependency between the input features and the output values [7]. The features selected based on the LASSO feature ranking method are useful for improving the performance of the fault identification system. Fig. 1. represent the methodology used for fault diagnosis.

![Figure 1. Flowchart for fault diagnosis using HHT](image)

![Figure 2. Bearing Test Rig](image)

2. Experimentation
To conduct the study, Case Western Reserve University (CWRU) bearing data with different rotating speed and fault conditions are considered in the present paper. The schematic diagram of experimental set up with accelerometer mounted on the bearing housing at the drive end of the induction motor, which is connected to a torque transducer, and coupled with dynamometer, is shown in Fig. 2. Signals are captured from the drive end of bearing with the different fault conditions as: (1) healthy bearing
(HB); (2) inner race fault (IR); (3) ball fault (BF); (4) outer race fault (OR) and variation in rpm of shaft are 1730, 1750, 1772, and 1797 rpm respectively [8]. A 6205-2RS JEM SKF deep-groove ball bearing is used for capturing signals from accelerometers, whose dimensions and specifications are referred from [9].

3. Hilbert-Huang Transform
Due to the non-stationary nature of ball bearing in operating condition, Fourier Transform is not considered as an effective technique for fault diagnosis. According to the limitation of Heisenberg-Gabor inequality, the resolution of the signal in the time domain and frequency domain simultaneously cannot be done with conventional signal processing techniques. To overcome these limitations time-frequency analysis method known as the Hilbert-Huang Transform (HHT) is used [4]. This method employs Empirical Mode Decomposition (EMD) on the non-stationary and non-linear signals into various IMFs. The decomposed signal has different components known as Intrinsic Mode Functions (IMF) which captures the instantaneous frequency data as time-dependent function.

4. Feature selection using LASSO
In order to reduce the amount of data to be handled and enhance the performance of the classification models, we can reduce the number features from the feature vector by checking the relationships of the features with the class variables. Feature selection methods provide various benefits such as less computation time, maximizing prediction accuracy, and selection of relevant features from the signals captured after conduction experiments. Robert Tibshirani [10] introduced the method of Least Absolute Shrinkage and Selection Operator (LASSO). The method uses a shrinking process also known as regularization to penalize the coefficients of variables. The variables also known as feature, in present study, which have nonzero coefficient after the application of shrinking process, are selected as a relevant feature. When numbers of features are more and numbers of experiments are less then LASSO is useful, since the variance is reduced without a substantial increase in the biasedness [11]. In this way overfitting problem is also reduced due to selection of relevant features. Tibshirani used the quadratic program (QP) for least square regressions in LASSO. Table 1 shows the features ranked in descending order as selected by LASSO.

5. Fault identification techniques
After selecting a relevant feature from the LASSO-based feature ranking technique, the accuracy of the methodology used is assessed with two different classifier using machine learning techniques. Support Vector Machine (SVM) is a machine learning model used for classification as well as regression problems. To maximize the margin, the SVM regression algorithm works. Margin is defined as the distance between the separating hyperplane and training samples which are close to the hyperplane known as support vectors [12]. In this study, since the feature vector is extracted from ball bearings so non-linear kernel function PUK is used to fit the maximum-margin hyperplane so as to accurately predict the class of the input feature set. Random Forest employs the ensemble learning method which comprises of a combination of single-level decision trees and arrives at decision-based on the voting of a random set of available decision trees. For instance, in the initial phase, two third samples are considered for training and the remaining one third is considered for validation. The process is repeated ten times if ten-fold cross validation is performed on classifier [2]. In the process of model building each decision tree cast a vote for one class, and finally the calculated votes are used to assess the generalization capability of the classifier.

6. Results and discussion
In the present work, training and tenfold cross-validation using SVM and Random Forest, has been done. The relevant feature according to LASSO based feature ranking is shown in Table 1. In tenfold cross-validation process, ten iterations are performed when the data set is divided into ten-sized folds in such a way that nine parts are used for training and remaining part used for testing. Total of 64 instances and 20 features are used for the study. The variation of training and tenfold cross-validation accuracies with respect to the number of features using SVM and Random Forest can be observed in...
Fig. 3. With the first eight features selected by LASSO feature ranking method 100% and 85.93% training and tenfold cross-validation accuracy respectively is achieved while using the SVM model. For the Random Forest model, first nineteen features were selected using the LASSO Feature ranking method and 100% and 96.87% training and tenfold cross-validation accuracy respectively was achieved which diagnose the fault with considerable accuracy. Table 2 shows the result obtained through training and tenfold cross-validation. It is observed that Random Forest gives better result as compared to SVM.

Table 1. Selected Features Using LASSO

| Sr. No | Feature Name                      | Sr. No | Feature Name       |
|--------|-----------------------------------|--------|--------------------|
| 1      | L Factor                          | 11     | Log Entropy        |
| 2      | Median                            | 12     | Form Factor        |
| 3      | Standard Deviation                | 13     | Shannon Entropy    |
| 4      | Mode                              | 14     | Shape Factor       |
| 5      | Peak to RMS                       | 15     | Norm Entropy       |
| 6      | Variance                          | 16     | RMS                |
| 7      | Peak to Peak                      | 17     | Kurtosis           |
| 8      | Signal to Noise and Distortion Ratio | 18     | Crest Factor       |
| 9      | Root Sum of Square                | 19     | Skewness           |
| 10     | Sure Entropy                      | 20     | Mean               |

Table 2. Training and Tenfold Cross Validation Accuracy

| Sr. No | Classifier Name          | No. of Features | Training Accuracy | Tenfold Accuracy |
|--------|--------------------------|-----------------|-------------------|------------------|
| 1      | Support Vector Machine   | 8               | 100               | 85.93            |
| 2      | Random Forest            | 19              | 100               | 96.87            |

7. Conclusion
In this paper, authors utilized a methodology to identify faults in bearings using HHT based signal processing technique, LASSO as a feature ranking method, and machine learning classification techniques. Twenty features are extracted through the HHT and then feature are ranked according to LASSO. The utility of features selected by LASSO feature ranking method provides a significant reduction in the number of features required for fault identification with satisfactory accuracy in diagnosing bearing faults. To diagnose the type of faults SVM and Random forest machine learning techniques used. Training and ten-fold cross validation performed on feature vector and it is observed.
that SVM and Random Forest classifiers gives 100% training accuracy to diagnose bearing faults with both SVM and Random Forest. Similarly ten-fold cross validation accuracy of 85.93% and 96.87% respectively achieved by utilizing eight and nineteen features respectively selected as per LASSO feature ranking method. The methodology used can be further compared with other signal processing methods and feature ranking techniques.

8. References
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