Journal of Mines, Metals and Fuels, *70(4) : 214-218; 2022. DOI: 10.18311/jmmf/2022/30060*

Print ISSN : 0022-2755

Journal of Mines, Metals and Fuels

Contents available at: www.informaticsjournals.com/index.php/jmmf

Bearing Fault Classification using Empirical Mode Decomposition and Machine Learning Approach

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Abstract

Industrial machinery often breakdowns due to faults in rolling bearing. Bearing diagnosis plays a vital role in condition monitoring of machinery. Operating conditions and working environment of bearings make them prone to single or multiple faults. In this research, signals from both healthy and faulty bearings are extracted and decomposed into empirical modes. By analyzing different empirical modes from 8 derived empirical modes for healthy and faulty bearings under different fault sizes, the first mode has the most information to classify bearing condition. From the first empirical mode eight features in time domain were calculated for various bearing conditions like healthy, rolling element fault, outer and inner race fault. The feature extraction of vibration signal based on Empirical Mode Decomposition (EMD) is extensively explored and applied in diagnosis of fault in rolling bearings. This paper presents mathematical analysis for selection of valid Intrinsic Mode Functions (IMFs) of EMD. These chosen features are trained and classified using different classifiers. Among them K-star classifier is most reliable to categorize the bearing defects.

Keywords: *Bearing Fault Detection, Empirical Mode Decomposition, K-star, Rolling Element, Vibration Signal*

1. Introduction

Rolling element bearing acts as one of the vital components in rotating machinery. Pitting and spalling are major common defects in bearings. Misalignment, lubrication failure, fatigue, poo fitting, contamination and corrosion are major reasons for bearing failure in rotating components. It is necessary to detect and fix these defects in initial phase to avoid fatal failure and damage of machinery (Tandon and Choudhury, 1999; Patil *et al.*, 2008).One of the popular technique for machine condition monitoring (Taylor, 2003; Scheffer and Girdhar, 2004) is vibration analysis. Common failures leave signs in raw vibration signal. These could be used with existing principles to design predictive maintenance systems.

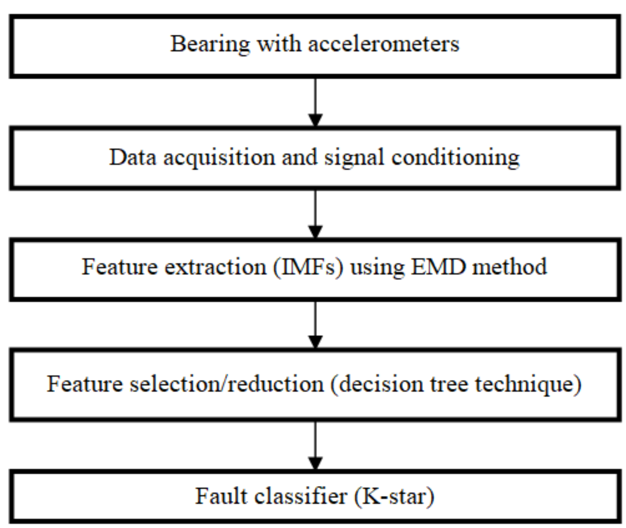

Figure 1. Flow chart of fault diagnosis of bearing with machine learning approach.

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Table 1. Energy feature vector evaluation based on EMD method

Class	Sample No.	Energy Feature Vector							
		V1	V2	V3	V4	V5	V6	V7	V8
Healthy	1	0.2848	0.6939	0.1651	0.0725	0.1467	0.3074	0.3801	0.3801
	2	0.3121	0.7692	0.1557	0.0790	0.1450	0.3116	0.2849	0.2849
Inner Race(0.1)	1	0.4868	0.7159	0.4226	0.2210	0.1033	0.0923	0.0448	0.0448
	2	0.3190	0.8011	0.4527	0.1871	0.0876	0.0703	0.0448	0.0448
Ball(0.1)	1	0.9069	0.4076	0.0763	0.0527	0.0399	0.0287	0.0145	0.0145
	2	0.8729	0.4712	0.0932	0.0499	0.0369	0.0283	0.0361	0.0361
Outer Race(0.1)	1	0.5273	0.7168	0.4546	0.0359	0.0102	0.0035	0.0035	0.0035
	2	0.4989	0.6975	0.5116	0.0527	0.0106	0.0035	0.0036	0.0036
Inner Race(0.3)	1	0.9886	0.1454	0.0327	0.0105	0.0093	0.0095	0.0067	0.0067
	2	0.9804	0.1902	0.0459	0.0138	0.0116	0.0088	0.0055	0.0055
Ball(0.3)	1	0.9662	0.2296	0.0369	0.0243	0.0534	0.0794	0.0358	0.0358
	2	0.9502	0.2642	0.0518	0.0360	0.0491	0.1314	0.0433	0.0433
Outer Race(0.3)	1	0.8329	0.5403	0.1046	0.0325	0.0311	0.0298	0.0156	0.0156
	2	0.8837	0.4594	0.0699	0.0197	0.0236	0.0228	0.0287	0.0287
Inner Race(0.5)	1	0.9973	0.0526	0.0123	0.0142	0.0160	0.0132	0.0306	0.0306
	2	0.9971	0.0711	0.0145	0.0078	0.0126	0.0068	0.0110	0.0110
Ball(0.5)	1	0.9601	0.2709	0.0583	0.0260	0.0169	0.0152	0.0104	0.0104
	2	0.9642	0.2599	0.0438	0.0216	0.0142	0.0106	0.0056	0.0056
Outer Race(0.5)	1	0.8937	0.4324	0.1012	0.0332	0.0374	0.0352	0.0118	0.0118
	2	0.8935	0.4284	0.1188	0.0295	0.0391	0.0340	0.0152	0.0152

Table 2. Comparison between various classifiers against classification accuracy and computational time

	Classifier	**Classification Accuracy (%)**	**Computational Time (Sec)**
1.	Artificial Neural Network	80	0.5
2.	Naïve Bayes	87	0.0
3.	Bayes Net	82	0.02
4.	Support Vector Machine	61.5	0.31
5.	K-Star	90	0.0
6.	Decision Tree	86.5	0.02

Traditionally, waveforms of fault vibration signals in time or frequency domain is used to detect faults in bearing (Peng *et al.*, 2005; Su *et al.*, 2010; Rafiee *et al.*, 2010; Feng *et al.*, 2011). Operating a defect bearing acts as a source of noise and vibration (Sunnersjo, 1978; Sunnersjo, 1985). Signals extracted from these bearings are neither linear nor stationary. This weakens feature extraction of fault information affecting accuracy of fault identification when the analysis is done in time or frequency domain. Targeting the problem, N.E. Huang (1998) proposed an EMD method which is a self–adaptive signal processing method for fault feature extraction of rolling bearings. EMD algorithm is used to decompose the signals into components with a well-defined instantaneous frequency called Intrinsic Mode Functions (IMFs). Figure 1 illustrates methodology with machine learning approach in fault diagnosis of bearing.

2. Experimental Set Up

Figure 2 shows line diagram of experimental set up. It is comprised 1 HP motor, bearing 1, bearing 2 with accelerometer and loading platform. Motor shaft is supported by end bearings. Single point faults were seeded to the test bearing (bearing 2) using laser cutting method. The fault diameter of 0.1mm, 0.3mm and 0.5mm were seeded individually at the inner race, rolling element and outer race.

Table 3. Confusion matrix of K-star algorithm with EMD features

A	B	C	D	E	F	G	H	I	J	CLASS
20	0	0	0	0	0	0	0	0	0	A- Healthy
0	20	0	0	0	0	0	0	0	0	B- Inner Race (0.1)
0	0	18	0	0	0	1	0	0	1	C- Ball (0.1)
0	0	0	19	1	0	0	0	0	0	D- Outer Race (0.1)
0	0	0	0	20	0	0	0	0	0	E- Inner Race (0.3)
0	0	0	0	0	18	0	0	0	2	F- Ball (0.3)
0	0	0	0	0	0	18	0	0	2	G- Outer Race (0.3)
0	0	0	0	0	0	0	20	0	0	H- Inner Race (0.5)
0	0	1	0	1	0	0	1	17	0	I- Ball (0.5)
0	0	1	0	0	0	9	0	0	10	J- Outer Race (0.5)

Test rig was reinstalled with faulted bearings and accelerometers (not shown) attached to the housing were used to collect vibration data. This experiment runs at constant load of 200 N and speed of 1200 rpm which is same as real time application.

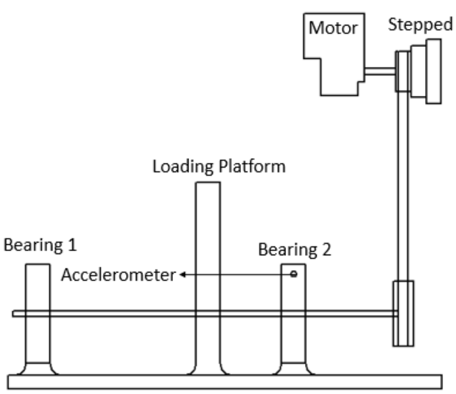

Figure 2. Line diagram of experimental set-up.

2.1 Data Analysis and Methods

2.2.1 Empirical Mode Decomposition

In 1998, Haung *et al.* (1998) proposed a method for signal analysis called as empirical mode decomposition (EMD) to deal with non-stationary and non-linear signals. In this method any complex signal is decomposed into a residual portion and several multi scale Intrinsic Mode Functions (IMFs). Each IMF is denoted by a function and must satisfy below two conditions.

1. Differences in the number of maxima and zero crossings must be less than or equal to one.
2. Average of upper envelope and lower envelope signal should be less than defined threshold values, which is equal to zero.

The detailed algorithm can be found in the article of Haung *et al.* (1998). The result of EMD algorithm will be numerous IMFs. Based on signal analyzed, number of IMFs might differ. From the set of IMFs extracted, few would have fault signal part which helps in identifying faults. Extracted features could be used independently or as inputs to fault diagnosis models.

Generally below mentioned problems are addressed with EMD method.

1. Finding relevant intrinsic mode functions of the signal.
2. Extraction of features relevant to faults from IMFs.
3. By using extracted features it establishes fault detection and diagnosis models.

2.2.2 Classification with EMD Features

The extracted vibration signals relevant to 10 different class of bearing, features are decomposed into several IMFs using EMD method. The amplitude energy feature vector is constructed using fault information which was dominantly present in first 8 IMFs and same was used to verify the performance of model proposed. Using equation T'= [E1, E2, E3… … En], feature energy vector is obtained and is provided as input vector to decision tree

(J48 algorithm). Table 1 shows energy feature vector (2 samples per class) evaluation based on EMD method.

3. Feature Reduction and Classification

Different fault conditions were induced to bearing and vibration signal were acquired. Overall vibration level could be determined with vibration signal analysis using time domain technique. But this doesn't provide diagnostic information. Hence EMD features were extracted from signals acquired and fed as input to J48 algorithm. K-star algorithm (Cleary, 1995) is used to classify different fault conditions from reduced features.

As shown in Table 1. EMD features are extracted in large number from signals. Not all the features extracted have relevant information. Accuracy of classifier is affected by irrelevant information making computation more difficult and wastage of system resources. J48 algorithm was fed with 8 EMD features as input. 2 among them were ignored as their contribution to classification was negligible. From extracted EMD features, 6 most significant contributors were identified using J48 algorithm. Machine learning was leveraged for classification of selected features using different classifiers. Table 2 provides information on classification accuracy and time required to classify the instances for the extracted EMD features.

Classification accuracy and time complexities are listed in Table 2 for different classifiers. Based on these parameters users would have to choose relevant algorithms for classification (Jegadeeshwaran and Sugumaran, 2014). In comparison to other classifiers K-star classifier needs less time for classification and yields high accuracy. Table 3 depicts confusion matrix of K-star algorithm with EMD features.

From Table 3, out of 200 samples only 20 instances are misclassified. This yields a classification efficiency of 90%, which is greater than other classifiers. With notably high classification efficiency, K-star classifiers with EMD features for fault diagnosis of bearing looks attractive.

4. Conclusions

In current study, an effort has been made to evaluate the suitability and capability of different classifiers for bearing condition monitoring. Vibration signals were acquired from different fault bearing conditions and were fed as input to MATLAB to extract EMD features. Different classifiers were used to compare the extracted features. Among them K-star classifier yields a classification efficiency of 90% which is promising for a high accuracy diagnosis of fault bearing. Hence could be used to monitor condition of bearing in various applications. Future research could focus on prediction of early faults in bearings by comparing different bearing conditions with different algorithms.

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