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Fault Diagnosis of Gearbox based on ITD-Tunable Q-Factor Wavelet Transform

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Gearboxes are an important part of the mechanical drives element that provides the several applications like automotive industry, wind turbine industry and power plant industry, *etc.* The condition monitoring of the gearbox reduces its operational cost, maintenance cost and avoid hazardous losses. The features selected forthe health status of the gearbox has important parameter to calculate classification accuracy. In the current study the intrinsic time-scale decomposition (ITD) and tunable Q-factor wavelet transform (TQWT) are used to diagnose the faults in the gear. The ITD method decomposed the input signal into the baseline signal with instantaneous parameters of signal and sequence of the proper rotation components (PRCs). The PRC of higher kurtosis value is the input signal for TQWT. The TQWT is a discrete wavelet transform and decomposed the vibration signals of the gearbox into sub-bands. The feature vector is calculated for each sub-band of the TQWT. The proposed approach is analyzed by the classification accuracy of the feature vector. The recommended method is evaluated using experimental data of 2009 PHM Data of gearbox under various health conditions. The SVM and KNN methods are investigated that the improved classification accuracy with ITD-TQWT model are 97.9% and 96.9% respectively.

Keywords: Fractal feature, Gearbox, Machine learning, Tunable Q-wavelet transforms

1 Introduction

Gearbox is the most critical elements in machinery components which are used to adjust speed or torque as per the requirement of several industries such as automobile and power plant. As the versatile many applications of gearbox, its fault detection and diagnosis is very important arena to detect the fault and its severity.

Tong *et al.*[1] advised that gear meshing frequency contains much information regarding the health state of gear. They use multi-input single-output (MISO) model to recognize the resonance agitated by impact and verified experimentally by taking forklift. Hu *et al.*[2]uses extreme learning machine for fault diagnosis of gearbox. The vibration signals of gearbox are decomposed by wavelet packet. The gearbox with different faults under variation of speed is analyzed by Sharma *et al*.[3]. The vibration signals are decomposed by vibrational mode decomposition (VMD). Li *et al.*[4] introduced optimized rational Hermite interpolation method to diagnosis of gear faults. Qin *et al.*[5] presented the wavelet transform for planetary gearbox which is M-band flexible transformation. The proposed methodology is verified by experimental also. The fault related mode extraction by empirical wavelet transform is established by Kong *et al.*[6]. The featuresvectors for several types of faults are calculated from envelope spectrums of the extracted modes. The proposed methodology is verified by experimental and simulation results. The intrinsic time scale decomposition (ITD) is the well-known technique to decomposed the vibration signals into proper rotational components (PRCs) with capability to overcome mode mixing and contain time-based information[7]. Hu *et al.*[8] investigatedan ensemble intrinsic time-scale decomposition (EITD) and fractal dimension to predict the fault type of gearbox. It is concluded that the proposed technique has a good noise cancellation capability and capable to extract operative features. The tunable Q-factor wavelet transforms are used by Upadhyay *et al.[9]* for fault diagnosis of ball bearings. The decomposition of vibration signal of bearing by TQWT shows good classification results by SVM with fractal features. He *et al.*[10] used TQWT with double Q-factor for the faults detection in the gearbox. The useful components of the noisy vibration signal of the gearbox are estimated by sparse optimization. The proposed methodologyis

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able to take out periodical transient component with high-resonance from signals of the gearbox. Teng *et al.*[11] uses the integrated concept of the effects of the TQWT and non-convex penalty with noise optimization for the correctly break down the raw vibration signal of the planetary gearbox into resonance components and noises. The resonance components of the vibration signals are capable to recognize the possible faults in the gearbox by using multi-stage envelope spectrogram. The usefulness of the projected methodology is confirmed by the simulated defective signal and experimental work with wind turbine.

In the present paper, ITD-TQWT technique is investigated to accurately predict the defects in the gearbox. The vibration signals produced by gearbox are decomposed by ITD into different PRCs. The PRC which has highest kurtosis value is the input signal for the TQWT. The constraints of the TQWT are the Q-factor, oversampling rate and decomposition level and represented by Q, r and J respectively. The constraints of the TQWT are selected by genetic algorithm to minimize absolute reconstruction error. The vibration signal of the gearbox which is obtained after ITD decomposes into several sub-bands by TQWT. Higuchi and Katz fractal dimension are calculated for all sub-band of TQWT. Besides of this, statistical features: mean, standard deviation, kurtosis and skewness of these sub-bands are also calculated. The feature vector is formed by the extracted features, which is used for the classification model of the machine learning methodology.

2 Methodology

Gearbox failure leads to breakdown of machines. The detailed understanding of the failure of gearbox required to mitigate downtime of machines in industries. For diagnosis of failure of gearboxes, the vibration signature analysis is most widely used technique. For vibration signature analysis of gearbox, firstly vibration signals of gearbox are extracted with the help of specified accelerometer. Secondly, specific features (mean, standard deviation, kurtosis, skewness, *etc.*) are obtained through these vibration signals. Based upon the selected features, a machine learning technique is investigated to categorize the types of faults. There are several machine learning technique[9] available in literature.The vibration signals obtained by gearbox are non-stationary, complicated and includes noise. This makes the thought-provoking of fault detection in gearbox. The main objectives of these techniques are to minimize cost and time for maintenance of gearbox and avoid breakdown.

The methodology adopted in this research is shown in Fig. 1.

2.1 Intrinsic time-scale decomposition

ITD is a methodology which is used for effective and accurate time frequency energy investigation of the rotational vibration signals. It is capable to deal with the non-static and irregular distinctive nature of the vibration signal of the gearbox. ITD decomposed the signal into PRCs and the result preserve the temporal information of the signal. The PRC contain information about frequency and predominant energy which is used to diagnose fault feature of the gearbox. The vibration signal of the gearbox 'x_g' with operator 'l', take out a baseline signal from x_g such that the residual to be a proper rotation.

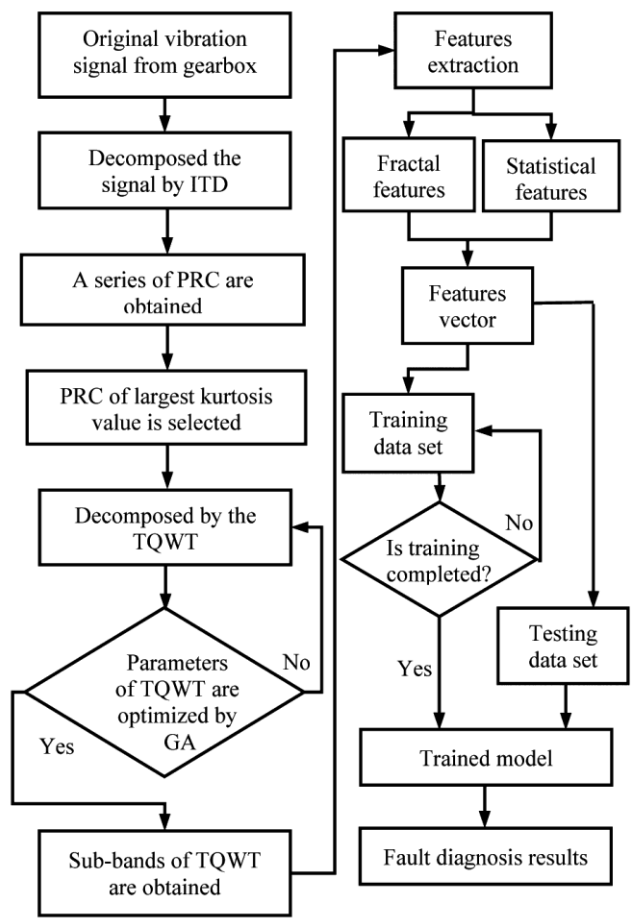

Fig. 1 — Scheme of the proposed methodology

$$x_g = lx_g + (1-l)x_g \qquad \ldots (1)$$

where lx_gbaseline is signal and $(1\text{-}l)x_g$is the proper rotation.

2.2 Tunable Q-factor wavelet transform

TQWT is a kind of wavelet convert of vibration signals in which Q-factor is tunable. These vibration signals are discrete time signals of gearbox which is obtained by accelerometer. It is supposed that the vibration signal can be disintegrated into n different components.

$$x = \sum_{i=1}^{n} x_i \qquad \ldots (2)$$

Here vibration signals 'x' can be decomposed into 'n' numbers of sub-bands with different oscillation distinctive. The input signal 'x_i' at each decomposition level, have sampling frequency f_s is decomposed into sub-bands that are low-pass sub-bands and high-pass sub-bands. The key constraints of TQWT are Q-factor, oversampling rate and number of levels which are denoted by Q, r and J respectively. The selections of these constraints are such that the maximum absolute difference between wavelet transforms and its inverse transforms is minimized. The Q-factor of the TQWT, measure the number of fluctuations that the wavelet reveals. The frequency resolution of higher Q-factor is improve compared to lower Q-factor.

The low-pass scaling factor (α) and high-pass scaling factor (β) are calculated by oversampling rate and Q-factor as[12]:

$$\beta = 2/(1+Q) \qquad \ldots (3)$$

$$\alpha = 1-(\beta/r) \qquad \ldots (4)$$

The oversampling rate decides the interpretation of the measurement of overlap of spectral occurs among nearby band-pass filters. It is known that oversampling rate is directly proportional to the overlap in band-pass filter. That means the value of the oversampling rate "r" increases with the increments in overlap in the spectral plot of the band-pass filters. The constraint 'J' is the measure of the quantity of the filter bank. The decomposition of the 'J' stage filter bank creates (J+1) sub-bands. The maximum number of the filter bank is restricted by the size of the input signal 'N' and scaling parameters of the filters (α *and* β):

$$J_{\max} = \frac{\log(\beta N/8)}{\log(1/\alpha)} \qquad \ldots (5)$$

2.3 Classification model based on machine learning

Several classification models which are based on machine learning, able to classify the vibration data based upon the selected features. Some example of machine learning models are support vector machine (SVM), artificial neural network (ANN), decision tree (DT), and k-nearest neighbor (KNN), *etc.* These models are based on the algorithm and adapted features from input data.

SVMs are influential and flexible algorithms for classification problems. It is based on the methodology that, to split the dataset into classes such that a maximum marginal hyper plane can be obtained. The hyper plane is created among the categories of the dataset and the data points adjoining to the plane are recognized as support vector.

KNN algorithm is the non-parametric algorithm based on features relationship approach. In this approach, all training data are used for testing phase. In KNN, K is the numeral of adjoining neighbors. The advantage of using KNN that, it performance is better with smaller number of features.

3 Experiments

The representational diagram of the gearbox is exposed in Fig. 2. The vibration signals are extracted with the help of accelerometers. The details of vibration signals are taken from 2009 PHM Gearbox Data[13]. The data acquisition system is Endevco, whose sensitivity is 10mv/g and the sampling rate is 66,666.67 Hz.The measured signal

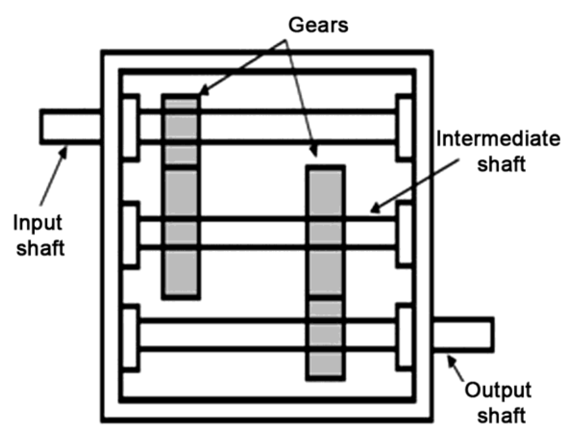

Fig. 2 — Test rig of gearbox

of gearbox contains of two accelerometer signal and one tachometer signal. The vibration signals of the gearbox have eight different labels, in which one is a healthy state of gearbox and remaining seven are different fault condition of the gearbox as shown in Table 1. The numbers of tooth on different four gears are 32, 96, 48 and 80 respectively. The five different speeds of input shaft are 30, 35, 40, 45 and 50 Hz with four different types of loading. Henceforth, total 160 samples are obtained consisting different health state of the gearbox with this experiment.

4 Feature Extraction

4.1 Fractal dimension features

Higuchi's fractal dimension(HFD)

Higuchi's fractal dimension is a qualitative measure of dynamics of vibration signals. The signal is considered as geometric entity[12]. Consider the vibration signal of gearbox is $\{y(1), y(2), y(3), \ldots\ldots. y(N)\}$, where 'N' is the number of the sample points in the signal. From the available signal of gearbox, a new signal of sample 'k' such that

$y_m^k = \{y(m), y(m+k), y(m+2k), \ldots\ldots.. y(m+Mk)\}$ and $M = (N-m)/k$ where $m = 1, 2, 3, \ldots\ldots., k$.

The average length L_m^k is

$$L_m^k = \sum_{j=1}^{M} (\left| y(m+jk) - y(m+(j-1)k) \right| (N-1)/Mk)/k \quad \ldots (6)$$

Next, the average length of the curve is calculated.

Katz's fractal dimension (KFD)

Katz's fractal dimension of the sample is calculated as [13],

$$FD = \frac{\log(S/A)}{\log(D/A)} \quad \ldots (7)$$

where, S and A are summed and mean of the Euclidean distance concerning the consecutive points. The distance between first point and target point is D.

Table 1 — Details of labels of gear

Gear type	Labels	Conditions
	1	Healthy
	2	Tooth chipped and gear eccentric
	3	Gear eccentric
	4	Gear eccentric and broken tooth
Spur	5	Tooth chipped and gear Eccentric and bearing fault
	6	Broken tooth and bearing faults
	7	Bearing faults
	8	Bearing faults and shaft imbalance

4.2 Statistical features

Statistical features[13] like mean, standard deviation, kurtosis and skewness are calculated by the equations 8-11. Considered the vibration signals of gearbox are $\{y_1, y_2, y_3 \ldots\ldots\ldots., y_N\}$, N is the number of discrete signal points and $\bar{y}$ is the mean of the signal.

$$Mean(\bar{Y}) = \frac{\sum_{j=1}^{N} Y_j}{N} \quad \ldots (8)$$

$$Sandard\ Deviation(\sigma) = \sqrt{\frac{\sum_{j=1}^{N} \left(Y_j - \bar{Y}\right)^2}{N-1}} \quad \ldots (9)$$

$$Kurtosis = \frac{\sum_{j=1}^{N} \left(\frac{Y_j - \bar{Y}}{N} \right)}{\sigma^4} \quad \ldots (10)$$

$$Skewness = \frac{\sum_{j=1}^{N} \left(Y_j - \bar{Y}\right)^3}{N} \quad \ldots (11)$$

5 Result and Discussion

In the present paper, PHM 2009 data sets for gearbox are used. The data set of gearbox has eight different labels, in which '1' represent healthy condition and remaining numbers shows different faults in the gearbox. There are five different speeds of input shaft and four types of loading, thus total twenty vibration sample for each case or label of gearbox are obtained. The data set for this experiment comprises 160 samples, including different labels of the gearbox. For each types of label vibration signal, two fractal features and four statistical features are calculated. Based upon these calculated features the model is trained. The classification accuracies are 86.9 % and 84.4 % by the model KNN and SVM respectively. For further improvements of the model performance, the raw vibration data obtained from the gearbox are decomposed by ITD and the series of PRCs calculated. The PRC whose kurtosis value is largest among other PRCs for each label of vibration signal is selected for further analysis purpose. The selected PRC is decomposed by TQWT as shown in Fig. 3 for all types of label vibration signal and sub-bands of vibration signals are obtained. For each sub-bands, features are calculated. The constraints

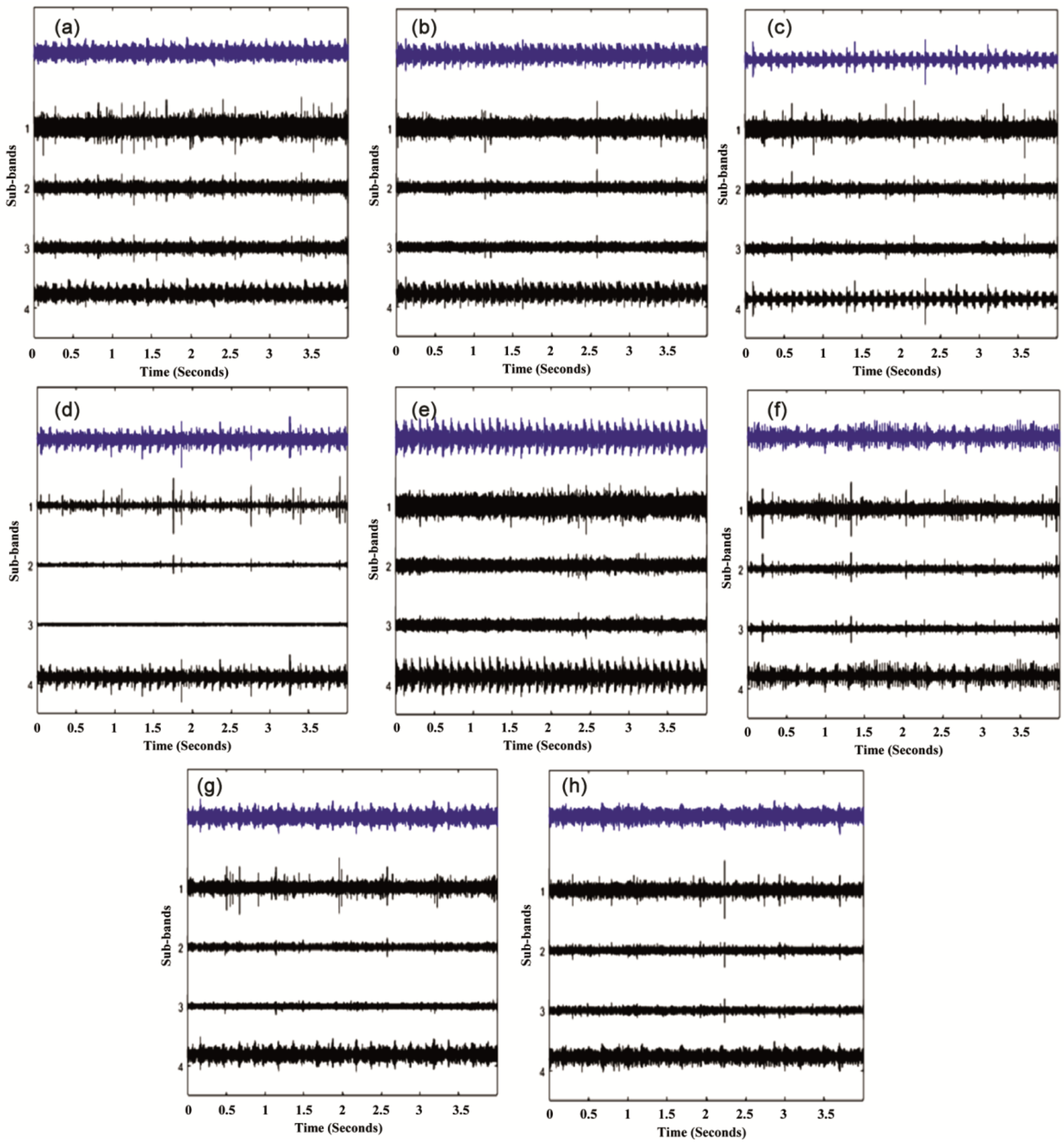

Fig. 3 — TQWT based decomposition of vibration signal of the gearbox (a) Label-1 (b) Label-2 (c) Label-3 (d) Label-4 (e) Label-5 (f) Label-6 (g) Label-7 (h) Label-8

of the TQWT are selected based on genetic algorithm. The dataset has now increased by 480 samples. The constraints ‘Q’, ‘r’ and ‘J’ are chosen such that it minimizes the maximum absolute difference between the original vibration signal and inverse TQWT of sub-bands of high entropy. The classification accuracy after decomposition by ITD-TQWT is 97.7 % and 96.9 % by SVM and KNN respectively. The effectiveness of ITD-TQWT is clearly analyzed and shown in Table 2. The confusion matrix is shown in Fig. 4.

Table 2 — Classification accuracy of different models

Methods	SVM	KNN
Features with ITD-TQWT	97.7 %	96.9 %
Features without ITD-TQWT	84.4%	86.9 %

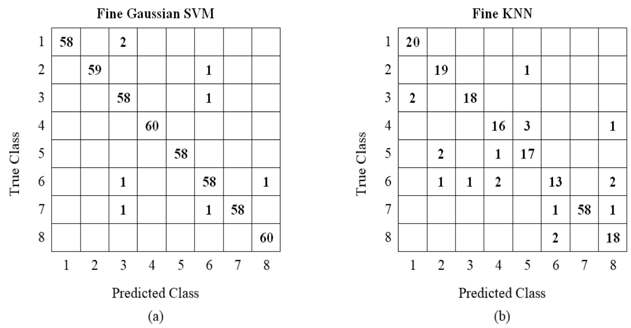

Fig. 4 — Confusion matrix (a) Features with ITD-TQWT (b) Features without ITD-TQWT

6 Conclusion

The following conclusions are obtained in the present paper,

- The classification accuracy of the gearbox is improved with the decomposition of vibration signals by ITD- TQWT.
- The signal decomposed by ITD contains temporal information of the signal.
- The TQWT is suitable for efficient diagnosis of gear's defects with small number of features.
- The proposed methodology eliminates the requirement of the feature selection technique.
- The SVM and KNN models are included the signal decomposition by ITD – TQWT technique to investigate the classification accuracy of the present gearbox is 97.7% and 96.9 % respectively.
- The SVM and KNN methods showed the classification accuracy for the without decomposition signal are 84.4% to 86.9% respectively.

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