Multi-stages helical gearbox fault detection using vibration signal and Morlet wavelet transform adapted by information entropy difference

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Abstract

Although the wavelet analysis is a powerful tool and has been widely used for the vibration signal based gearbox fault diagnosis, there are some limitations that undermine its application. The results of the wavelet transform do not possess time invariant property, which may result in the loss of useful information and decrease the accuracy of fault diagnosis. Other limitations in wavelet transform are the selection of the suitable threshold and the wavelet function. A main challenge of wavelet analysis is the adaptability of the parameters of the mother wavelet to the time variance of the given signal. To overcome this deficiency, an adaptive Morlet wavelet transform method based on the information entropy optimization is proposed in this study. The proposed wavelet transform method is applied for analyzing the vibration signals to detect and diagnose the faults of a helical gearbox. A comparative study of the proposed method and the previous study which used the kurtosis maximization to adapt the wavelet parameters are also carried out to evaluate the proposed method

1. Introduction

Gearboxes are widely used to transmit the power and convert the speed in rotary machinery such as power generators, wind turbines and rotary aircrafts (Chorafas, 1990). In gearbox, gears mostly operate under high different operating condition demands, such as high operating speed and applied load (Smith, 1983). However, there is an increase in failure of gear components due to an excessive wear in gear rotating elements, lack of gear lubrication and material fatigue. Gearbox failures may lead to the personal injury, remarkable financial losses and sometimes may even lead to catastrophic consequence and plant shut down (Elbarghathi et al., 2012). Monitoring the condition of the gearbox component as early as possible provides advantages in the safety, operation and avoidance the consequence of any catastrophic accidents (Dapliaz et al., 2000).

Many methods based on the statistical parameters in the time domain and the frequency domains of vibration signals have been employed for gear fault detection and diagnosis. However, the vibration signals of gearboxes are very noisy and non-stationary. Therefore, the vibration statistical parameters in the time and frequency domains unable to give full information about location severity of faults because they could not suitable for non-stationary signal (Stevens et al., 1996; Randall, 1982; Stevens et al, 1996). In order to deal with this problem, several methods of time-frequency domain have been considered by researchers for gearbox condition monitoring and diagnosis such as short time Fourier transform (Combet et al., 2007; Cohen, 1995), wavelet transform (WT) (Staszewski et al., 2007), Wigner-Ville distribution (Ville, 1948), etc. Among these, WT is widely used for complex class of rotating machine where signal-to-noise ratio (SNR) and a large number of frequency components are present (Hubbard, 1998). However, there are some disadvantages in the use of WT such as the selection of the threshold and the optimization of the wavelet mother functions. Application of wavelet mother function optimization can be found in study of Younghua (Younghua et al., 2011) who used the modified Shannon wavelet entropy to optimize central frequency and bandwidth parameters of wavelet Morlet function. The results of the experiment analysis and application into signal denoising indicated that the proposed method had better denoising performance than other traditional WT. Chen et al. (Chen et al., 2005) proposed another method for optimizing wavelet parameters using

GA for the fault diagnosis of water hydraulic motor. The results of the experiment signal shows the characteristic vibration signal details in fine resolution.

In this study, a denoising method based on an adaptive Morlet WT where its parameters are optimized by using maximum Shannon entropy difference is proposed for fault diagnosis of gearboxes. This method is used for extracted features of two stage helical gearboxes with faulty condition of 30%, 60% and 100% tooth breakage. Firstly, time synchronous averaging (TSA) is used to remove the noise in a repetitive signal. The SNR of vibration signal can be improved significantly by suppressing the components which are asynchronous with that of interesting. Traditionally, this requirement is met by using an external trigger signal provided by a shaft encoder, and the revolution period of rotating machinery can be obtained. Then, the vibration signal is divided into small segments according to the revolution period of the rotating part, and all the segments are summed up together so that no coherent components and asynchronous components are cancelled out. Normally, vibration signals from rotating machinery are a combination of periodic signals with random noise. Secondly, maximum Shannon entropy difference is introduced to optimize central frequency and bandwidth parameters of the wavelet Morlet functions so as to perform optimal match with the impulsive components. The results of this technique will be compared to those of the maximum kurtosis principle.

2. Theoretical Background

2.1 Time Synchronous Averaging (TSA)

TSA is an effective technique in the time domain to remove the noise in a repetitive signal and is a widely used technique in vibration monitoring and fault diagnosis (Combet et al., 2007; Zakrajsek et al., 1993). Assuming that a signal $x(t)$ consists of a periodic signal $x_T(t)$ and a noisy component $n(t)$, the period of $x_T(t)$ is T_0 whose corresponding frequency is f_0, thus the signal can be expressed (Xingjia et al., 2009).

$$x(t) = x_T(t) + n(t) \qquad (1)$$

The synchronous average of the signal $x(t)$ by using TSA can be expressed as

$$y(t) = \frac{1}{M}\sum_{i=0}^{M-1} x(t + iT_0) \qquad (2)$$

where M the number of the average segments is $y(t)$ is the averaged result.

2.2 Definition of Morlet wavelet

The adaptive wavelet algorithm used in this study can be found in reference (Xingjia et al., 2009) in details. Wavelet transformers are inner products between signals $x(t)$ and the wavelet family. The wavelet transform of a signal $x(t)$ is defined as

$$WT_x(a,b) = \frac{1}{\sqrt{a}}\int x(t)\psi^*\left(\frac{t-b}{a}\right)dt \qquad (3)$$

where $x(t)$ is the signal, "*" denotes the complex conjugation, a is scale factor and b is shifting factor. The factor $1/\sqrt{a}$ is used to ensure energy preservation. $\psi(t)$ is the mother wavelet. The wavelet coefficient $WT_x(a,b)$ represents the similarity between the signal $x(t)$ and a wavelet (Yonghua et al., 2011).

There are different types of wavelet function for different use, which is very important task to select the proper wavelet for a specific signal. In this work, Morlet mother wavelet function is used because of the fault occurs and exists in the rotary component such as gearboxes are periodical impulse which is similar to Morlet wavelet. A Morlet wavelet and its Fourier transform as follow:

$$\psi_r(t) = \frac{1}{\sqrt{f_b\pi}}\exp\left(\frac{-t^2}{f_b}\right)\cos(2\pi f_c t) \qquad (4)$$

$$\psi(af) = e^{-\pi^2 f_b (af - f_c)^2} \qquad (5)$$

where f_b is the bandwidth parameter, f_c is the central wavelet frequency.

2.3 The procedure of optimizing Morlet wavelet parameters based on maximum entropy difference

It is obvious from equation (4) that the shape of the Morlet wavelet can be controlled by parameters f_b and f_c to balance time-frequency resolution. In this paper, the wavelet Shannon entropy is applied for choosing these optimum values. Assume $d(k), k = 1,2,..., N$ are wavelet coefficients of the signal $x(i), i = 1,2,..., N$. After normalization, the wavelet entropy can be defined as (Lin et al., 2002):

$$H = -\sum_{k=1}^{N/2} \bar{d}(k)\log(\bar{d}(k)) \qquad (6)$$

where $\bar{d}(k)$ are the normalized wavelet coefficients:

$$\bar{d}(k) = \frac{d(k)}{\sum_{k=}^{N} d(k)} \tag{7}$$

The procedure of using maximum entropy for optimizing the values of f_b and f_c is expressed as follows:

(i) Varying the parameters f_c and f_b within preselected intervals to produce different mother wavelets.

(ii) Perform wavelet transform for baseline and fault signal using each mother wavelet and calculate the entropy difference between the two condition signals.

(iii) Compare the maximum entropy difference value. The parameters f_c and f_b that correspond to the maximum value are the best parameters to use to reveal the fault features.

(iv) Repeat step (i)-(iii) to choose parameters for the three faulty cases 30%, 60% and 100% at different operating load conditions.

(v) Finally, do the fault diagnosis with the maximum entropy difference value.

2.4 The procedure of optimizing Morlet wavelet parameters based on maximum kurtosis principle

Kurtosis can be used as the performance measure of a Morlet wavelet filter (Lin et al., 2002). The definition of kurtosis is

$$Kur(y) = E(y^4) - 3[E(y^2)]^2 \tag{8}$$

where y is the sampled time series and E represents the mechanical expectation of the series. The procedure to perform the adaptive wavelet filtering is as follows:

(i) Varying the parameters f_c and f_b within preselected intervals to produce different mother wavelet.

(ii) Perform wavelet transform using each mother wavelet and calculate the maximum kurtosis of each outcome.

(iii) Compare the kurtosis value. The parameters f_c and f_b that correspond to the largest kurtosis are the best parameters to use to reveal the hidden fault features.

3. Experiment

3.1 Test rig facilities

The gear test apparatus shown in Figure 1 was used for this research work because in addition to its widespread use in industry such gears allow faults to be easily simulated. The test rig consisted of an induction motor, two stage helical gearbox, coupling and mechanical load. The two-stage helical reduction gearbox was driven by an 11kW, 1465rpm, four poles, and 3-phase induction motor. A pair of helical gear with 1.45 contact ratio was used in the test. The driving gear has 58 teeth and the driving gear has 47 teeth. The motor speed and load was controlled by variable speed drive for studying condition monitoring performance under operating conditions.

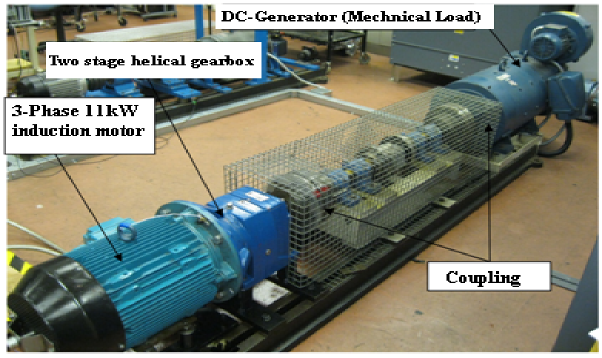

Figure 1 Experimental test rig of gearbox

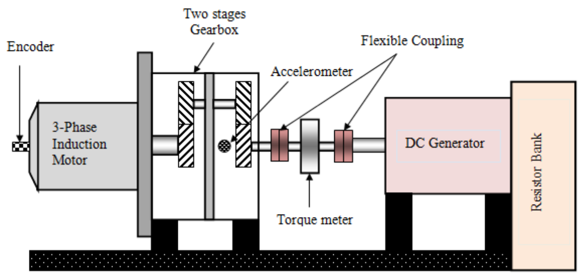

Figure 2 Schematic diagram of test rig

3.2 Data acquisition system

Vibration signal was measured by accelerometer (type PCB 338C04) with sensitivity of 100mV/g, and frequency response range is from 1Hz to 20 kHz. It was mounted on gearbox housing casing as indicated in Figure 2. The optical encoder was mounted at the end the motor, which provide a one-pulse per revolution signal. All signals from the sensors were properly amplified, and then fed into anti-aliasing filters sets. The filter cut-off frequency for the vibration signal was set high enough to capture the fourth harmonic of gear meshing frequency, whereas the cut-off frequency for the reference signal 15kH to reduce pulse wave distortion after the filter. Each transducer produces a voltage output which is proportional to the amplitude of the measured parameters and then connected to the data acquisition system by coaxial BNC cables. The data acquisition instrument used in the test was the model PD2-MF-16-500/16L PCI board which has 16 analogy input channels. The sampling rate is 500 kHz for each channel with 16 bit data resolution and the input voltage range is ±10V.

3.3 Gear faults

In this study, three degrees of the tooth breakage: 30%,60% and 100% tooth damage as shown in Figure 3, are simulated to examine the sensitivity of adaptive wavelet analysis. They were produced by removing the percentage of the tooth face on the pinion gear in the width direction. Vibration signals collected from a same gearbox in which the two broken gears were tested once a time. The larger fault of 100% tooth breakage is for understanding the potential characteristics of wavelet transform and the 30% tooth brokerage is interested in this study to evaluate the performance wavelets in fault detection.

a) 30% tooth breakage

b) 60% tooth breakage

Figure 3 Gear faults

4. Results and discussion

4.1 TSA Pre-processing

Vibration and the encoder signals are collected simultaneously at different operating condition. Both signals were collected by DAS for four cases gear fault 30%, 60%, 100% and one is considered as healthy baseline at sample rate of 100 kHz. In all fault cases, the data was collected at different loads: 9.09%, 18.2%, 31.8%, 54.5% and 77.3% of the full loads, respectively. However, the speed was in full speed (1465rpm), the duration time was 16 second for each collection which has 1600000 points. This data length is sufficient for random noise suppression in TSA technique which is introduced to this work to reduce the noisy in the signal. The encoder is mounted in the end of DC motor shaft in order to measure the shaft speed and is the reference for synchronous average of the vibration signal. However, due to the oscillation of the shaft speed which caused that a time interval of pluses in the encoder signal is not constant. The angular acceleration is computed thought the arrival times of the closet three pulses known from the sampling of the encoder signal, then, the correct placement of the resample on the time axis is carried out based on the constant angular acceleration is performed based on the accurate placement of the resample. In this work, the time axis resampling is processed in section with per section 1000 points and 5 sections are selected. As the resample times are computed, the vibration signal is resample according to the resample time's axis for synchronous average. Figure 4 shows TSA signals for three cases gear faults 30%, 60% and 100% tooth brakeage are compared with baseline is the healthy case for gearbox operates under different loads as follow 9.09%, 18.2%, 31.8%, 54.5% and 77.3%. From Figure 4, the amplitude of the vibration signals increases with the increasing of the loads for three faulty cases. Moreover, the impulse components of the vibration signals are remarkable for all the test condition. However, for the faulty cases of 60% and 100% tooth damage are more and clear indications of fault. The TSA signals are showed much clearer indication of the 60% and 100% tooth breakage compared with baseline. On the other hand, the TSA signal between baseline and 30% tooth damage does not show that much difference for gear fault indication.

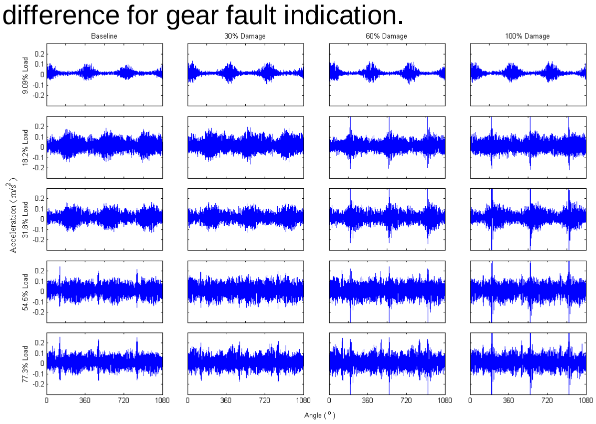

Figure 4 TSA vibration signals under different operating conditions and gear

4.2 Feature extraction of adaptive Morlet wavelet analysis based on maximum entropy difference and maximum kurtosis principle

In this work, an adaptive Morlet transform is selected to analysis the TSA vibration signals collected under different faulty cases of baseline, 30%, 60% and 100% tooth breakage were operated under different operating condition. These wavelet are all orthogonal wavelet with faster, perfect reconstruction and non-redundant decomposition and used in many application. In this study, a new method based on adaptive Morlet wavelet is applied to extracted features for multi stage gearbox vibration signals, the modified Shannon entropy is used to optimize central frequency f_c and bandwidth frequency f_b parameters of Morlet wavelet to perform an optimal match with the impulsive component. However, this new method is compared with adaptive Morlet parameters optimization based on the kurtosis maximum principle. The TSA vibration signals of 5000 data points are selected to perform adaptive Morlet wavelet analysis for all the test condition to explore the joint time scale feature. Adaptive Morlet wavelet coefficients for both methods are presented with contour plots of maximum entropy difference and maximum kurtosis adaptive wavelet for baseline, 30%, 60% and 100% were operating under different loads and full operating speed (1465rpm).

From Figure 5 and 6, it can be seen that the adaptive wavelet coefficient image pattern are clearly different for different four cases as healthy, 30%, 60% and 100% tooth damage operating under different load operating condition as follow 9.09%, 18.2%, 31.8%, 54.5% and 77.3%. The periodic feature can be clearly seen the wavelet coefficient result in good frequency resolution both low and high frequency which shows the indication of fault for three cases comparing with the baseline Figure 5 for all operating loads. As shown in Figure 6, the meshing frequency are clearly visible at scale 5 and 20, the varying resolution on the time-frequency plane is due to the in the size of the wavelet during the analysis.

The gearbox signal at different condition cause the distribution of peak amplitude value to stretch towards the higher frequency region and appear at different time unit and frequencies in the contour. Compared with maximum kurtosis shown in Figure 7, it can be seen that there are clear differences between the baseline and 60 and 100% tooth damage but is not clear for 30% for all loads as follow 9.09%, 18.2%, 31.8%, 54.5% and 77.3% compare with minimum entropy adaptive wavelet. In particular, the wavelet coefficients of minimum entropy were much higher with larger visible area.

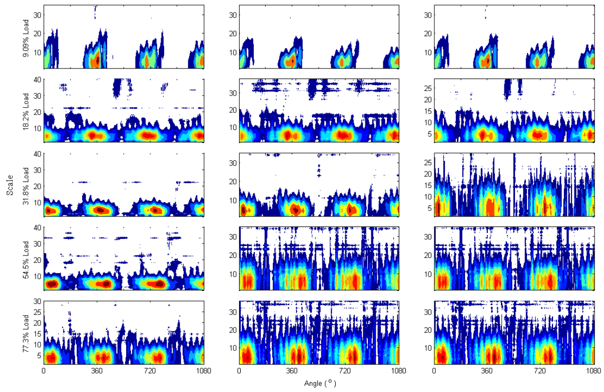

Figure 5 Contour plots of maximum entropy adaptive wavelet coefficient for different baseline gears

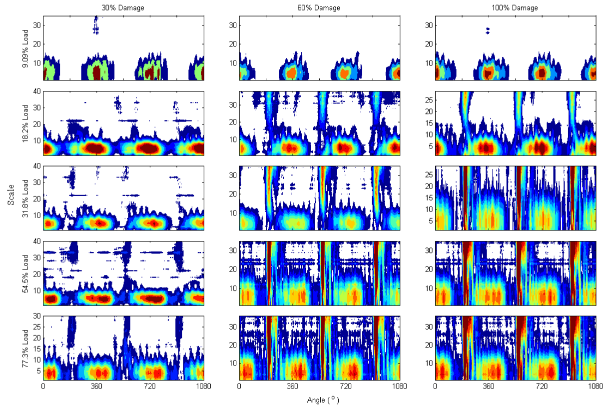

Figure 6 Contour plots of maximum entropy adaptive wavelet coefficient for fault different gear cases

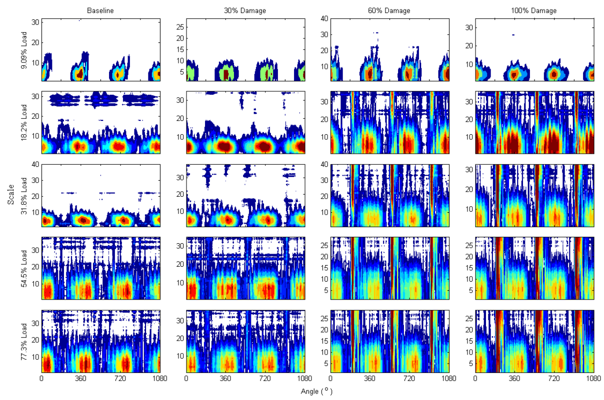

Figure 7 Contour plots of maximum kurtosis adaptive wavelet coefficient for different gear cases

For more detailed comparison as shown in Figure 8, it can be seen the value maximum entropy difference are clearly difference for four cases as healthy, 30%, 60% and 100% tooth damage operating under different load operating condition as follow 9.09%, 18.2%, 31.8%, 54.5% and 77.3%. Moreover, from Figure 8, it can be seen that the maximum kurtosis cannot show clear difference for all four cases. That are clear difference between baseline with 60% and 100% tooth damage but is not clear for 30% for all loads, compare with the maximum entropy adaptive wavelet, from the results as shown in Figure 8 shown that the proposed method based on adaptive Morlet wavelet using parameters optimization is much better than the method of adaptive Morlet based on the kurtosis maximisation.

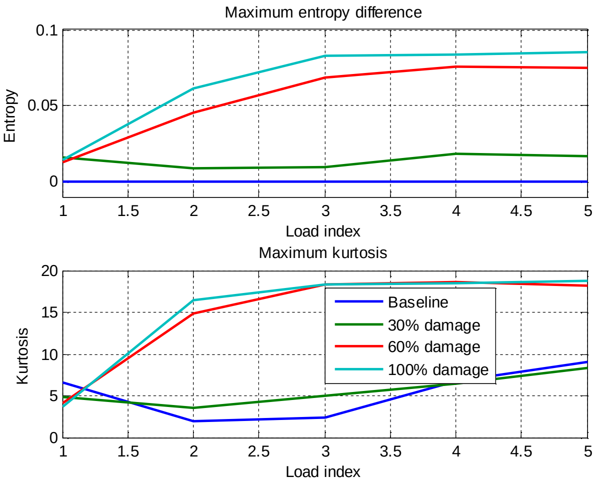

Figure 8 Maximum entropy difference and maximum kurtosis value of TSA vibration signal

5. Conclusions

A new adaptive Morlet wavelet method based on maximum wavelet entropy difference is proposed in this paper. It has been shown to be an effective tool for rotating machinery fault detection and diagnosis. In this study, the fault detection of multistage helical gearbox has been carried out by using adaptive Morlet wavelet and TSA method. TSA has removed the noisy component and showed the fault related impulse component which paves the basis for accurate feature extraction. Next, maximum Shannon entropy difference is used to optimize the central frequency and bandwidth parameter of the Morlet wavelet in order to achieve optimal match with impulsive components, to extract the features of the gear faults in the multistage of helical gearbox. The results show that the proposed method is much better than the method of adaptive Morlet based on the kurtosis maximisation.

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