Fault Diagnosis of Rolling Bearing under Variable Speed Conditions using Multisynchrosqueezing Transform

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Abstract: Fault diagnosis of rolling bearing has always been the focus of engineering research. Under variable speed conditions, the fault characteristic frequency will change with time. Time-frequency analysis method is an effective tool for studying time-varying signals, but the traditional time-frequency analysis method is easy to generate a plane with low time-frequency resolution and poor energy concentration, which is difficult to meet the requirements of practical applications. In this paper, we introduce a recently developed time-frequency post-processing technique, called multisynchrosqueezing transform. By performing multiple SST operations, this method can greatly improve the time-frequency energy concentration and obtain a satisfactory representation. Finally, this method was used to diagnose the rolling bearing faults in variable speed conditions successfully, and the effect was better than the traditional time-frequency analysis methods.

1. Introduction
As an important part of mechanical equipment, once the rolling bearing fails, it will cause the machine to run abnormally or even stop. Therefore, fault diagnosis of rolling bearing has always been the focus of our attention. Due to the requirements of actual work, rolling bearing will inevitably undergo stages of acceleration and deceleration. Compared with constant speed, fault diagnosis of rolling bearing under variable speed is more challenging [1-3].

Time-frequency (TF) analysis (TFA) methods are suitable for processing time-varying signals. They can characterize the features of these types of signals on a time-frequency/scale plane, which makes it widely used in biomedicine and radar [4, 5]. The traditional TFA methods, such as short-time Fourier transform (STFT), wavelet transform, Wigner-Ville distribution, have been studied for a long time. It is extremely difficult for them to be further applied in actual work since the rough TF resolution, external and internal interference. The TF distribution post-processing technique is developed based on them, which greatly improves the performance of traditional TFA methods. Synchrosqueezing transform (SST) [6] is one of the most popular techniques now. By squeezing the energy of the original TF spectrum along the frequency direction, it can not only improve the energy concentration of time-frequency representation (TFR), but also reconstructed the signal along the time direction. However, this method still has some shortcomings. When encountering a rapidly changing signal, the generated TFR by SST will appear energy blur and divergence [7, 8].
In this paper, we introduce a newly developed method, multisynchrosqueezing transform (MSST) [9]. This method is the further development of SST. By squeezing the TF spectrum energy to the true bandwidth of the signal several times, MSST can effectively solve the energy ambiguity and divergence problems of the original SST when processing fast time-varying signals. Finally, we successfully applied this method to the fault diagnosis of rolling bearing under variable speeds. The experimental results show that MSST can extract the fault characteristic frequency better compared with the traditional STFT and SST.

2. Methodology

In this section, we first introduce the related theory of SST. Then we give the theory of MSST.

2.1. SST

A signal usually contains multiple amplitude and frequency-modulated components, which can be modeled as

\[ y(t) = \sum_{k=1}^{N} y_k(t) = \sum_{k=1}^{N} A_k(t) e^{j\varphi_k(t)} \]  

The SST is developed based on the STFT. The STFT of \( y(t) \in L^2 \) with respect to the window \( g(t) \) is defined as

\[ G(t, \omega) = \int_{-\infty}^{\infty} y(u) g(u-t) e^{-j\omega(u-t)} du \]  

The core idea of SST is to reassign the TF coefficients of signals along the frequency direction, namely: \((t, \omega) \rightarrow (t, \tilde{\omega}(t, \omega))\), where \( \tilde{\omega}(t, \omega) \) is the estimated instantaneous frequency (IF) and can be calculated by Eq. (3).

\[ \tilde{\omega}(t, \omega) = \frac{\partial G(t, \omega)}{\partial G(t, \omega)} \]  

Therefore, we can get the SST of signal \( y(t) \) as

\[ V(t, \eta) = \int_{-\infty}^{\infty} G(t, \omega) \delta(\eta - \tilde{\omega}(t, \omega)) d\omega \]  

2.2. MSST

For pure harmonic signals, SST can estimate its IF accurately. However, for fast-changing signals, the IF estimator of SST is always biased. In addition, we must admit that one SST operation can greatly improve the energy concentration of spectrum \( G(t, \omega) \). Then consider performing more and more SST operations on the last time received result, which will be the core of MSST. According to the above analysis, MSST can be expressed by

\[ V^{[N]}(t, \eta) = \int_{-\infty}^{\infty} V^{[N-1]}(t, \omega) \delta(\eta - \tilde{\omega}^{[N]}(t, \omega)) d\omega \]  

where \( N \geq 2 \) and \( V^{[N-1]}(t, \omega) \) denotes the \((N-1)th\) SST operation result. However, it is very time-consuming to perform SST operation one time, let alone perform \( N \) times. Fortunately, we can calculate the IF estimator of the MSST first, and then perform once SST operation to \( G(t, \omega) \), which can get the same effect to Eq. (5). This method can greatly reduce the computer execution times. And the formula of this MSST can be expressed by

\[ V^{[N]}(t, \eta) = \int_{-\infty}^{\infty} G(t, \omega) \delta(\eta - \tilde{\omega}^{[N]}(t, \omega)) d\omega \]  

where \( \tilde{\omega}^{[N]}(t, \omega) \) denotes the IF estimator of MSST, which is calculated by Eq. (7).

\[ \tilde{\omega}^{[N]}(t, \omega) = \varphi'(t) + \left( \frac{\varphi''(t)^2}{\varphi''(t)^2 + 1} \right)^N (\omega - \varphi'(t)) \]  

Some research has proved that MSST has a very good effect in improving the energy concentration of TFR, and the specific derivation process of the MSST can be found on [9].

3. Fault diagnosis using MSST

In order to verify the potential of MSST for practical applications, we will use MSST to deal with different health conditions of vibration signals in this section. The experiment [10] is carried out with a machinery fault simulator (Figure 1). AC drive and accelerometer are used to control rotation speed and collect vibration data, respectively. It contains a healthy ER16K ball bearing and an experimental
bearing in the experiment. According to the parameters of ER16K bearing, we can obtain the inner and outer fault characteristic coefficient are 5.43 and 3.57, respectively. The sampling time and frequency are 5 s and 200 kHz.

Besides, in order to make the results more objective, we will use Renyi entropy as an evaluation index of the concentration of TFR. A lower Renyi entropy means a better-concentrated TFR. The Renyi entropy of order \( \alpha \) for a TFR \( H(t, \omega) \) was defined as

\[
r = -\frac{1}{1-\alpha} \log_2 \left( \frac{\int |H(t, \omega)|^\alpha d\omega}{\int |H(t, \omega)| d\omega} \right)
\]  

(8)

where \( \alpha \) is set to 3 in this work [11].

3.1. Detection of outer ring defect

In the first case, an outer ring fault bearing was used as experiment bearing. The bearing speed is increased from 13.3 Hz to 19.8 Hz gradually. The waveform of the collected signal is shown in Figure 2. It can be found that the signal amplitude gradually increases with time.

In order to extract the fault information contained in the vibration signal more effectively, the envelope signal is obtained by envelope demodulation first. Then we use MSST (\( N = 10 \) will be used in this paper) to process the envelope signal, the corresponding result is shown in Figure 3. In this result, we can easily locate the TF ridges of \( F_o \) and \( 2F_o \), which has great TF resolution and energy concentration. So, we can conclude that there is a fault in the outer ring of this bearing. In addition, Figure 4 shows the results of STFT and SST. From the figure, we can observe that they have very poor TF energy concentration and exist energy divergence problem. The upper left corner of these figures also shows the Renyi entropy of different TFRs. It is found that Renyi entropy of MSST result is the smallest, which further verifies the advantage of MSST.
3.2. Detection of inner ring defect

In the second case, the inner ring fault vibration signal is collected. The speed is reduced from 20.6 Hz to 13.6 Hz, and the time waveform is shown in Figure 5. The results obtained by MSST, STFT, and SST are shown in Figures 6 and 7, respectively. From the results, it is found that the MSST plane has lower Renyi entropy, better TF aggregation and resolution compared with STFT and SST results. In addition, based on $F_i$ and $2F_i$, we can determine that the bearing inner ring exists a fault.
4. Conclusion

Fault diagnosis of rolling bearing is the key research content of structural health monitoring of mechanical equipment. We introduce a newly developed TFA method, multisynchrosqueezing transform in this paper. Finally, we successfully extracted the fault characteristic frequency of rolling bearing and located the bearing fault location using this method.

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