Enhanced Fault Detection of Rolling Element Bearing Based on Cepstrum Editing and Stochastic Resonance

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Abstract. By signal pre-whitening based on cepstrum editing, the envelope analysis can be done over the full bandwidth of the pre-whitened signal, and this enhances the bearing characteristic frequencies. The bearing faults detection could be enhanced without knowledge of the optimum frequency bands to demodulate, however, envelope analysis over full bandwidth brings more noise interference. Stochastic resonance (SR), which is now often used in weak signal detection, is an important nonlinear effect. By normalized scale transform, SR can be applied in weak signal detection of machinery system. In this paper, signal pre-whitening based on cepstrum editing and SR theory are combined to enhance the detection of bearing fault. The envelope spectrum kurtosis of bearing fault characteristic components is used as indicators of bearing faults. Detection results of planted bearing inner race faults on a test rig show the enhanced detecting effects of the proposed method. And the indicators of bearing inner race faults enhanced by SR are compared to the ones without enhancement to validate the proposed method.

1. Introduction
Rolling element bearings are widely used in mechanical transmission systems. Their localized faults or damages usually produce characteristic frequency components, whose frequencies depending on bearing geometry, rotation speed and position of the faults[1]. Prognostics of rolling element bearing mandates detecting bearing defect signatures as early as possible, so that catastrophic accident or machine breakdown can be avoided. The success of bearing life prediction relies on accurate defect detection and assessment. However, because characteristic signals of bearing faults contain little energy and are usually annoyed by vibration noise, detection of characteristic frequency components has become one of the key technologies of early fault diagnosis and prognostics for rolling element bearing.

Stochastic resonance (SR) is a nonlinear effect that is now widely used in weak signal detection under heavy noise circumstances. Conventional signal processing method based on SR mainly focuses on small parameter signals[2-4], which does not satisfy the practical application. Generally, large parameter signal detection is carried out by noise intensity tuning and nonlinear system parameters tuning. In practice, tuning noise intensity is not always feasible. And the output SNR obtained by adjusting system parameters can exceed what is obtained through tuning noise intensity. In this paper,

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large parameter signal processing is realized by normalized scale transform based on SR system parameters tuning.

The classical model of SR includes nonlinear system, white noise and weak driving signal. But the white noise is always not the practical case in vibration signal of rolling element bearing. And there is often some unwanted discrete frequency components existing in the spectrum, with which the diagnosis of bearings is interfered. These discrete frequency components in low frequency range would be enhanced by SR unwillingly. Randall proposed a new method for separating discrete components from a signal based on cepstrum editing [5], and where after an even more drastic editing in the cepstrum, signal pre-whitening, is proposed [6]. The pre-whitening of vibration signal of bearing eventually results in a white signal, which contains both noise and non-stationarities (including the impulses resulting from localized bearing defects), but no discrete frequencies, such as from gears. Harmonics of bearing characteristic frequencies may be enhanced by envelope analysis on the whole frequency range of the pre-whitened signal without knowledge of optimum frequency bands. However, envelope analysis over full bandwidth brings more noise interference [6]. We find that the pre-whitened signal is nearly the ideal input of the SR system. The impulses in pre-whitened signal could be enhanced by SR system further.

In this paper, a new enhanced method of bearing diagnosis based on cepstrum editing and SR is proposed. Firstly the vibration signal of rolling element bearing is pre-whitened based on cepstrum editing. Then the envelope of residual signal is processed by SR system. The SR system parameters are tuned via normalized scale transform. The local kurtosis around bearing characteristic frequencies in spectrum is used as an indicator of bearing damage. Finally, vibration signals from bearings with planted-in inner race faults in a machinery fault simulation test rig was processed, and the result validated the enhancement effect of the proposed method.

2. Basic SR model and normalized scale transform

2.1. Basic SR model

The counterintuitive SR phenomenon is caused by cooperation of signal (deterministic force) and noise (stochastic force) in a nonlinear system. In a certain nonlinear system, noise plays a constructive role, and energy flows from noise to signal. When noise or system parameters are tuned properly, the SNR will reach a maximum. The SR has been theoretically developed in nonlinear bistable systems. A classical bistable model of SR can be described as the over-damped motion of a Brownian particle by Langevin equation:

\[ \ddot{x}(t) + \dot{x}(t) = -\frac{dU(x)}{dx} + s(t) + n(t) \]  

Where top script dots denote the time derivative. If the system is over damped, the inertial \( \ddot{x}(t) \) term can be neglected. \( s(t) = A \sin(2\pi f t) \) is the periodic driving signal and \( n(t) \) is the noise term. For simplicity, we define the noise term as zero-mean Gaussian white noise, and \( \langle n(t)n(t + \tau) \rangle = 2D\delta(\tau) \). Here, \( \langle \bullet \rangle \) represent average operator, \( \delta(t) \) is the delta function, and \( D \) denotes the noise intensity. Rescaling the system gives the motion equation as follows:

\[ \dot{x}(t) = -\frac{dU(x)}{dx} + s(t) + n(t) \]  

The \( U(x) \) is the bi-stable potential function having the form of a reflection-symmetric quartic [4]:

\[ U(x) = -\frac{1}{2} ax^2 + \frac{1}{4} bx^4 \]  

(3)
With \( a > 0 \) and \( b > 0 \), the system (2) is bi-stable, and there are two stable states at \( x_{1,2} = \pm \sqrt{a/b} \), one unstable state at \( x_0 = 0 \). By substituting \( U(x) \) of equation (3), equation (2) can be rewritten as

\[
\dot{x}(t) = ax - bx^3 + (s(t) + n(t))
\]  

(4)

The input signal of the bi-stable system model is \( s(t) + n(t) \), and the output signal is system state \( x(t) \).

2.2. Normalized Scale Transform

Consider the bi-stable dynamic SR model that can be depicted by stochastic differential equation (4), where \( a \) and \( b \) are positive and adjustable. By defining the transformation of coordinates as \( z = x\sqrt{b/a} \), \( \tau = at \), equation (4) is reformed as

\[
a\sqrt{\frac{a}{b}} \frac{dz}{d\tau} = a\sqrt{\frac{a}{b}} z - a\sqrt{\frac{a}{b}} z^3 + (s(\frac{\tau}{a}) + n(\frac{\tau}{a}))
\]  

(5)

According to the Gaussian white noise character, the term \( n(\tau/a)n(0) \) follows \( n(\tau/a)n(0) = 2Da\delta(\tau) \). Define \( \langle \xi(\tau) \rangle = 0 \), \( \langle \xi(\tau), \xi(0) \rangle = \delta(\tau) \), then \( n(\tau/a) = \sqrt{2Da}\xi(\tau) \). Equation (5) can be reformed and simplified as

\[
\frac{dz}{d\tau} = z - z^3 + \sqrt{\frac{b}{a}} \left( s(\frac{\tau}{a}) + \sqrt{2Da}\xi(\tau) \right)
\]  

(6)

Equation (6) is the normalized form of equation (4). Although equivalent compared to equation (4), the target signal frequency of equation (6) is reduced to \( 1/a \) times. The choice of parameter \( a \) is significant for high frequency signal detection.

For discrete signal, noise intensity \( D \) can be written as \( D = \sigma^2h/2 \), where \( h = 1/f \) is the sampling step. Noise variant RMS is \( \sigma_0 = \sqrt{2D/h} \), but after normalization, the noise intensity is changed to \( 2Db/a^2 \). Meanwhile the sampling step is \( a \) times as before. So noise variant RMS will be changed to \( \sigma = \sqrt{2Db/(a^2 \cdot ah)} \). Obviously, the RMS noise intensity ratio is \( \sigma/\sigma_0 = \sqrt{b/a^2} \) after and before the scale transformation. By comparison of equation (4) and equation (6), equation (4) could be transformed to the model with system parameters of \( a = b = 1 \), which we call it the normalized form, after the input signal multiplied a factor \( \sqrt{a^2/b} \).

There are four steps for practical application of normalized scale transform to detect weak signal detection: (1) for a frequency \( f_0 \ll 1 \), find the optimal noise intensity \( \sigma_0 \) with system parameters \( a_0 = b_0 = 1 \), such as \( \sigma_0 = 5 \) for \( f_0 = 0.1 \text{Hz} \) when signal amplitude \( A = 0.5 \); (2) make sure that the target signal frequency \( f \) is much lower than the sampling frequency to stabilize the detection model, and choose system parameters \( a = b = f/f_0 \); (3) amplify the system input signal by factor \( K = \sqrt{a^3/b} \cdot \sigma_0/\sigma = a\sigma_0/\sigma \), where \( \sigma \) is the actual noise intensity; (4) solve the differential equation of the conventional SR equation (4) with the amplified input signal and new parameters \( a \) and \( b \). By normalized scale transform, high frequency signal detection model is matched to the optimal detection model with system parameters \( a = b = 1 \) for small parameter signal. That is to say, the detection model is transformed to optimal. Actually, the optimal system parameters determined by the above four steps are suitable for a target signal of frequency range up to \( f \). For practical use, the target signal frequency could be set to high boundary of the interested frequency range.
3. Enhanced bearing fault detection method and indicator

It is known that using the cepstrum could remove discrete frequencies and thus could separate gear from bearing signal without the need for order tracking\cite{6}. The procedure proposed in [5] is to use editing (liftering) in the real cepstrum to remove selected components from the log amplitude of the original signal, and then combine the edited amplitude with the original phase spectrum to return to the time domain. Signal pre-whitening can be achieved by setting the real cepstrum of the original signal to zero, except at zero quefrency to maintain proper scaling; restore the original phase and inverse transform back to the time domain\cite{6}.

The enhanced rolling element bearing fault detection method we proposed is to pre-whiten the vibration signal based on cepstrum editing, and then put the envelope signal into the SR model to enhance the impact components caused by bearing fault. Pre-whitening the signal based on cepstrum editing could enhance bearing fault detection without knowledge of optimum frequency bands. And the eventual result of signal pre-whitening is a white signal, which is nearly the optimum input of classical SR model. The impact signal contained in the white signal could be enhanced further by SR model via normalized scale transform. The enhanced method based on combination of cepstrum editing and SR is shown in Figure 1.

![Figure 1. Schematic diagram of the enhanced bearing fault detection method.](image)

After the residual signal of pre-whitening enveloped over the full bandwidth, the enveloped signal is enhanced by SR, and the final result would be shown in frequency domain. We use the local kurtosis around bearing fault characteristic frequency in spectrum as an indicator to compare the results of the proposed method and the method of just pre-whitening. Here the local kurtosis of spectrum is also termed SK for short.

4. Experiments and results

The proposed method is applied to vibration signal from machinery fault simulation test rig shown in figure 2. Tests were carried out on the test rig with good and planted-in inner fault bearings. The test rig is driven by a variable-speed electric motor. For these tests, the motor was running at 628 RPM, with two rotor disks on the shaft. The Bearing1 in figure 2 is alternated with good bearing, bearing with 0.2-3.2 mm different size planted inner race faults, which are shown in figure 3. Signals were measured by an accelerometer on the casing immediately above it. Details of the geometry of the bearings with the expected fault frequencies are given in table 1. The raw vibration data were collected with the sampling rate 50 kHz. And two second data were collected. Figure 4 displays the recorded raw time signals from Accelerometer1 denoted in figure 2, in the case of (a) a good bearing, (b) a bearing with 0.2mm inner race fault and (c) a bearing with 0.5mm inner race fault. The other raw vibration data of 0.8-3.2 mm different size inner race faults will not be shown in this paper for consideration of succinctness.
**Figure 2.** Machinery fault simulation test rig.

| Dimensions                  | 0.2 mm | 0.5 mm | 0.8 mm | 1.1 mm |
|-----------------------------|--------|--------|--------|--------|
| Speed of shaft (RPM)        |        |        |        | 628    |
| Bearing roller diameter(mm) |        |        |        | 7.50   |
| Pitch circle diameter(mm)   |        |        |        | 34.50  |
| Number of rolling elements(n)|        |        |        | 11     |
| Contact angle(deg)          |        |        |        | 0      |

**Characteristic fault frequencies(Hz)**

|                          |        |        |        |        |
|--------------------------|--------|--------|--------|--------|
| Ball pass frequency outer, BPFO | 44.87  |        |        |        |
| Ball pass frequency inner, BPFI | 70.27  |        |        |        |
| Ball Spin frequency, BSF  | 22.57  |        |        |        |
| Fundamental train frequency, FTF | 4.08   |        |        |        |

**Table 1.** Test bearing characteristics parameters.

**Figure 3.** The inner races with different size planted faults.
Figure 4. Raw vibration signals of good bearing (a), bearing with 0.2mm inner race fault (b) and bearing with 0.5mm inner race fault (c).

The characteristic frequencies of the test bearings are listed in table 1. Figure 5 shows the residual signal of good bearing after signal pre-whitening based on cepstrum editing and its envelope spectrum. The residual signals and their envelope spectra of bearings with 0.2mm and 0.5mm inner race faults are shown in figure 6 and figure 7. The BPFI and its first and second harmonics are marked by red ‘*‘ in all the spectra. The BPFI and its harmonics could be found in figure 6(b) and figure 7(b). We calculated the SK around BPFI as the indicator of bearing inner race damage status. The curve of inner race fault size vs. the SK indicator is depicted in figure 8. The inner race faults bearings could be differentiated from good one. But the curve fluctuates widely. And the uptrend of the curve is not obvious.

Figure 5. Pre-whitening residual signal of good bearing (a) and its envelope spectrum (b).

Figure 6. Pre-whitening residual signal of bearing with 0.2mm inner race fault (a) and its envelope spectrum (b).
Figure 7. Pre-whitening residual signal of bearing with 0.5mm inner race fault (a) and its envelope spectrum (b).

Figure 8. The curve of bearing inner race fault size vs. SK indicator.

Then we put the residual envelope signal after pre-whitening into the SR model and got the output signal via normalized scale transform. Figure 9. shows the corresponding spectra of the three signals after the data processing procedures according to schematic diagram depicted in figure 1. The SR system parameters were tuned as the procedures in section 2 with a target signal frequency of 200 Hz. It is found that the BPFI components of all the bearings with inner race faults were enhanced differently. The curve of SK indicator vs. inner race fault size is depicted in figure 10. We could see the uptrend of the SK indicator curve with inner race fault size, though there are still some fluctuations. The diagnosis result of the proposed method is more robust.

Figure 9. Envelope spectra of good bearing (a), bearing with 0.2mm inner race fault (b) and bearing with 0.5mm inner race fault (c) processed by the proposed method.
Figure 10. The curve of bearing inner race fault size vs. SK indicator, processed by the proposed method.

5. Conclusions
An enhanced bearing fault diagnosis method is proposed based on the combination of signal pre-whitening and SR. The signal pre-whitening is carried out based on cepstrum editing. The method is robust and suitable for the application with more vibration interference. The inner race fault diagnosis example validates the method. The curve of SK indicator vs. inner race fault size indicated out an obvious uptrend despite some fluctuation.

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