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Original Citation

Xu, Yuandong, Tang, Xiaoli, Gu, Fengshou, Ball, Andrew and Gu, James Xi (2017) Early Detection of Rolling Bearing Faults Using an Auto-correlated Envelope Ensemble Average. Proceedings of the 23rd International Conference on Automation & Computing, (University of Huddersfield, 7-8 September 2017). (In Press)

Proceedings of the 23rd International Conference on Automation & Computing, University of Huddersfield, Huddersfield, UK, 7-8 September 2017

Early Detection of Rolling Bearing Faults Using an Auto-correlated Envelope Ensemble Average

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***Abstract*—Bearings have been inevitably used in broad applications of rotating machines. To increase the efficiency, reliability and safety of machines, condition monitoring of bearings is significant during the operation. However, due to the influence of high background noise and bearing component slippages, incipient faults are difficult to detect. With the continuous research on the bearing system, the modulation effects have been well known and the demodulation based on optimal frequency bands is approved as a promising method in condition monitoring. For the purpose of enhancing the performance of demodulation analysis, a robust method, ensemble average autocorrelation based stochastic subspace identification (SSI), is introduced to determine the optimal frequency bands. Furthermore, considering that both the average and autocorrelation functions can reduce noise, auto-correlated envelope ensemble average (AEEA) is proposed to suppress noise and highlight the localised fault signature. In order to examine the performance of this method, the slippage of bearing signals is modelled as a Markov process in the simulation study. Based on the analysis results of simulated bearing fault signals with white noise and slippage and an experimental signal from a planetary gearbox test bench, the proposed method is robust to determine the optimal frequency bands, suppress noise and extract the fault characteristics.**

Keywords—bearing; fault detection; auto-correlated envelope ensemble average; SSI

I. INTRODUCTION

Bearings play an important role in the field of rotating machinery and the failure of bearings may result in the breakdown of machines or even catastrophic accidents. In order to maintain the efficiency, safety and reliability of machines, application of condition monitoring (CM), accessing the health condition of machines by periodic monitoring, is effective to prevent failure and avoid its consequences. With the continuous investigation of the bearing system, the high frequency resonance technique (HFRT), later called ‘‘envelope analysis’’, was developed [1] owing to the outstanding ability of the good resolution after the frequency shift from high carrier frequency bands to low fault frequency bands. Since the technique of high frequency demodulation was introduced by Darlow, plenty of research has been explored to make demodulation analysis[2]. As Antoni [3] studied spectral kurtosis (SK) thoroughly, Fast Kurtogram [4] based on short-time fast Fourier transform (STFT) and wavelet transform (WT) has been developed and explored by many researchers[5], [6]. Gu [7] introduced modulation signal bispectrum (MSB) to identify and quantify the common faults of a compressor. Tian [8] and Rehab [9] verified modulation signal bispectrum (MSB) with high performance of robustness to detect the optimal bands and bearing faults even though the signal-to-noise ratio (SNR) is very low.

System identification techniques have been employed to thoroughly understand the dynamics of bearings. A series of models [10]–[14] were developed to simulate the vibration of bearings with local defects. Based on the understanding of the outputs and inputs, the determination of the proper frequency bands is the identification of the natural frequencies. Therefore, the system identification methods can be used to choose the carrier frequencies automatically and SSI, using output-only vibration measurements, has attracted numerous researchers for decades and the real breakthrough of SSI algorithms is introduced in [15]. Continually, a reference-based covariance driven SSI was generalised by Peeters and De Roeck [16]. Then, improvements and expansion[17]–[20] on this algorithm have been carried out. In this paper, a novel method, ensemble average autocorrelation based stochastic subspace identification (SSI) was developed to automatically select the optimal bands according to the characteristics of modulation signals.

Usually the phase information of vibration induced by rotating machines is constant with the shaft rotating but the impulsive behaviours of rolling element bearings with localized defects are approximately periodic owing to the randomly varying slippage[5], [21]. Assuming that there is no slippage between components, theoretical fault frequencies of bearings with different faults are calculated by the impacts on the corresponding components.

This paper is supported by China Scholarship Council.

However, a slight slippage of 2% happens in the practical working conditions[21]. In this paper, the effect of slippage between bearing elements is also explored in the simulation study. To address the problem, an auto-correlated envelope ensemble average (AEEA) method is developed to tolerate the slippage of the bearing components.

This paper is arranged as follows: the second section mainly introduces the novel method; next, a vibration signal induced by a rolling element bearing with a local defect is simulated and the noise-free signal with high-level noise and randomly phase is used to examine the performance of the proposed method; in the third portion, the bearing tests are presented and the novel method is also employed to extract the fault signature from the experimental signals; and lastly the conclusion is made to highlight the performance of the method in the field of denoising and fault detection.

II. Auto-Correlated Ensemble Average Based Stochastic Subspace Identification

Vibration from a bearing with defects is usually of amplitude modulation signal [10]. This is resulted from the interactions between the periodical impulses and system resonances. However, the signal often submerged in various noises such as measurement systems and nearby vibration sources. Especially, when the fault is at its early stage, the modulation feature is very small and make it difficult to detect. Therefore, effective noise reduction methods are required to enhance the modulation features. The authors suggested [22] to use the autocorrelation ensemble average which is applied to the filtered signals for noise and aperiodic interference suppression and allows an implementation of higher sensitivity and robustness detection of small bearing faults.

A further study shows that the bearing vibration signals could also consists of phase modulation noises. Although rolling bearings are designed to operate under pure rolling process for reducing frictions between raceways and rolling elements, it enviably undergoes small relative sliding between the races and elements because of various random impacts, load variations, local deformations and lubrication status changes. In addition, the sliding may become more obvious when bearing radial clearances become larger with service life time when the bearing is more likely to start local fatigue defect. This small sliding causes random variations between the periods of impulses and exhibits as phase modulations, leading to a lower signal to noise ratio.

In order to enhance the robustness of system identification, the auto-correlated envelope ensemble average is considered to be the inputs instead of the raw vibration signals [22] and the following procedure is referred to the conventional covariance driven stochastic subspace identification. Hence, ensemble average autocorrelation [23]–[25] based stochastic subspace identification [18], [26]–[28] (EAAC-SSI) is employed to supress noise and determine the optimal band for demodulation analysis and the main steps of the method are shown in the first portion of Fig. 1.

Based on the optimal frequency bands selected by the novel method automatically, the filtered vibration signal is then divided into short segments with the same length. Then, the envelope of the segments are obtained by Hilbert transform. As autocorrelation is able to enhance the periodic impulses [29] and the white noise decays to zero quickly [30], the autocorrelation function is employed to supress noise and detect faults. Hence, the autocorrelation functions of segment envelope are calculated. Since the auto-correlated envelopes of segments are acquired, the amplitude spectrum of the average autocorrelation of the envelope is computed to demonstrate the fault features. The procedure of the demodulation method is detailed in the second part of Fig. 1.

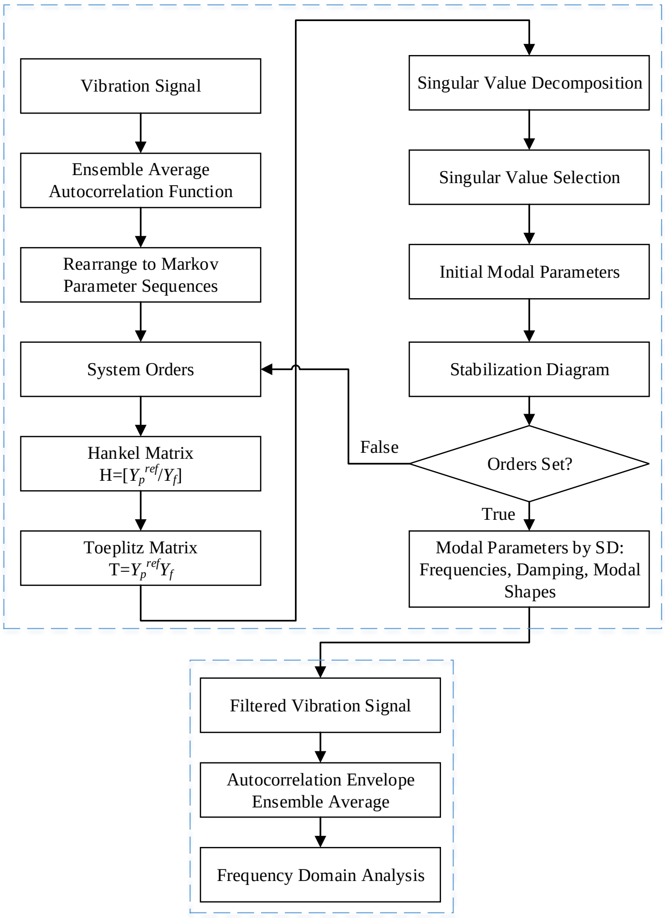

Fig. 1. Flow chart of EAAC-SSI and AEEA

III. Simulation Study

In order to examine the effectiveness of the novel approach, the bearing signal simulation is carried out. A defective bearing signal is a typically amplitude modulation signal [10]. The vibration signal of a bearing system with a local fault consists of periodical impulses, system resonance and noise. Hence, it can be expressed as equation (1).

$$x(t) = h(t) * u(t) + n(t) \tag{1}$$

where, $h(t)$ is the impulse system response, which consists of the system resonant behaviours; $u(t)$ is periodic impacts induced by the rolling element passing the defects; $n(t)$ is the inevitable noise which results from the working environments and the data acquisition system.

It is simple to generate the modulation signal based on equation (1). However, the vibration including fault information is a phase-lock signal and it cannot indicate the slippage of bearings in the practical working condition. Additionally, the slippage between bearing components is a typical Markov process. Consequently, the random slippage at each impact is simulated and the array of impacts is rearranged to a Markov chain, which is expressed as follows.

$$t_i = t_{i-1} + T_f + t_{s(i)} \quad i = 1, 2 \cdots N \tag{2}$$

where, t_i is the moment of the i_{th} impact; T_f is the cycle of impacts; and $t_{s(i)}$ is the random slippage at i_{th} impact.

As a result, the impact array satisfying Markov property is generated. According to the different level slippage, the bearing vibration with local faults can be simulated more practically.

TABLE I. KEY PARAMETERS

Parameters	***Symbol***	***Value***
Sampling Rate	Fs	96,000 Hz
Natural Freuency	f_{rs}	5400 Hz
Fault Frequency	f_f	89.8 Hz
Data Length	t	90 s

As shown in TABLE I, key parameters of the simulated bearing signal are listed and the waveform of the periodic signal is depicted in Fig. 2. As aforementioned, two cases--white noise and slippage--were investigated in the simulation study and the following contents give details of the results from the novel approach and the average spectrum of conventional envelope analysis.

A. High level white noise

The influence of white noise is inevitable in the procedure of fault detection and the ambient working condition of rotating machines generates large quantities of noise and results in the failure of incipient fault detection. Accordingly, the robustness of the novel method to the influence of high level noise is studied.

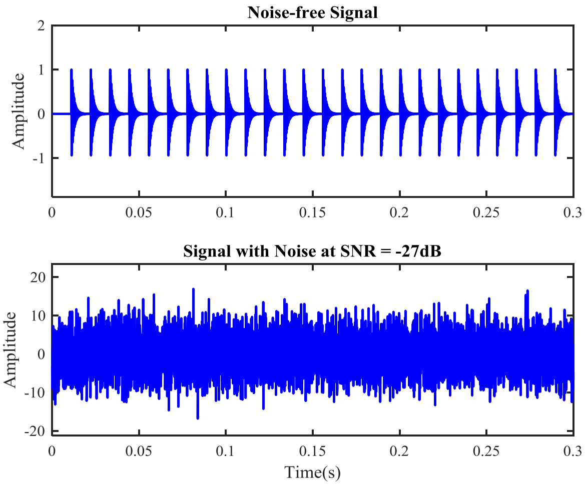

Fig. 2. Typical time waveform of the simulated signal

Fig. 2 demonstrates the temporal waveform of the noise-free signal and the second inset shows that the periodic signal with fault information is submerged by the high level noise at -27dB. In order to benchmark the proposed fault detector, the average spectrum of conventional envelope is employed to extract fault features. Based on optimal bands selected by EAAC-SSI, the filtered signal with bandwidth 600Hz is obtained and then divided into the same length subdivisions. Next, the envelope spectrum of each segment signal is calculated and finally, the average spectrum of conventional envelope is acquired. In order to compare the results of two methods, the spectra are normalized to illustrate the effectiveness.

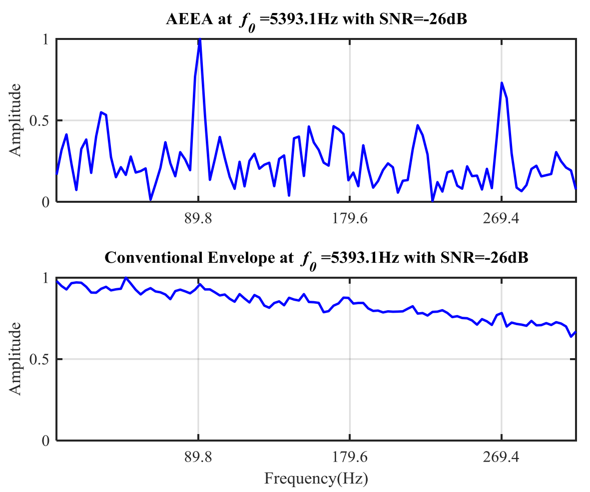

Fig. 3. Normalized envelope spectrum by AEEA applied to noisy signal

As shown in Fig. 3, EAAC-SSI automatically determines the optimal centre frequency 5393.1Hz, which is the carrier frequency of the modulation signal and based on the proper frequency band, auto-correlated envelope ensemble average clearly highlights the fault frequency 89.8Hz and its corresponding 3rd harmonic. However, conventional method fails to detect the defects even with the application of the optimal bands. Therefore, EAAC detector is more reliable and accurate than the conventional envelope spectrum.

B. *Random slippage*

Practically, the bearing elements (the shaft, inner race, rolling elements, outer race, and the housing) are not fixed in the motion. According to reference [21], approximate 2% slippage happens to lead to the randomness of the phase. In this section, the cyclostationary signal is simulated based on a Markov phase chain.

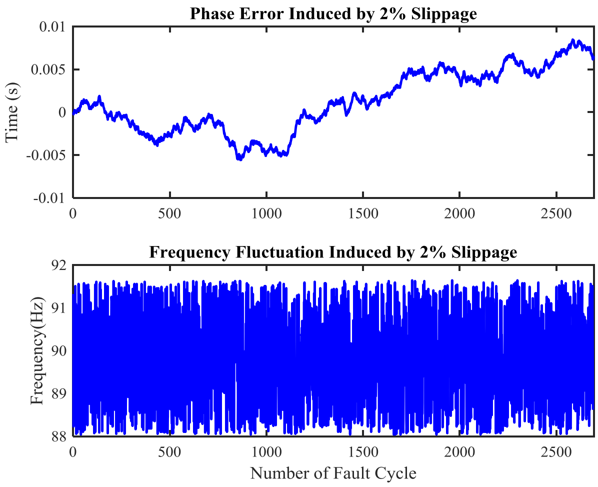

Fig. 4. Random phase and frequency due to slippage

The frequency fluctuation induced by the slippage is shown in Fig. 4. Owing to the occurrence of the slippage, the theoretical fault frequency is unstable. The simulated bearing vibration with slippage and noise is processed by two methods and the spectra are depicted in Fig. 5.

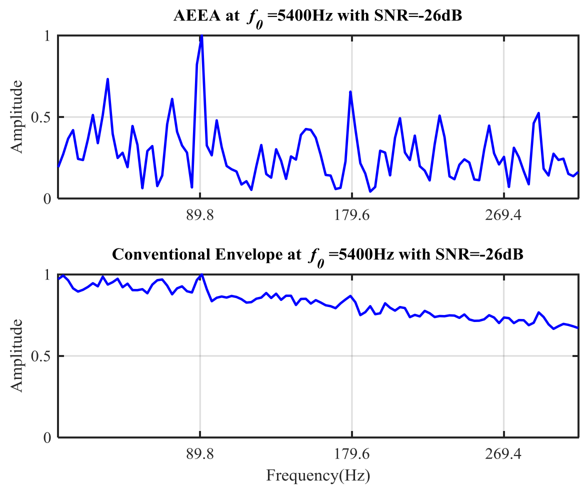

Fig. 5. Normalised envelop spectrum by applying AEEA to slippage signal

As the strong interference of amplitude and phase modulation, the EAAC-SSI fails to extract the natural frequencies. However, based on the optimal frequency bands selected manually, Fig. 5 indicates that AEEA is effective in fault detection of cyclostationary signals with high level noise at SNR of –26dB. Auto-correlated envelope ensemble average shows the fundamental fault frequency and the second harmonic while the benchmark one only shows the information of strong white noise. The ability of AEEA to resist the effects of phase modulation and Gaussian is still robust, whereas the average convention envelope spectrum shows little details about the fault characteristics.

In the simulation study, the proposed method is employed to tackle the bearing signal with high level noise and high percentage of slippage and the results show that AEEA is a more reliable and more accurate method to detect the early faults.

IV. Experimental Evaluation

For the purpose of benchmarking the novel method, different simulated signals were generated to be the inputs. As the examination is completed, an experimental signal from a test rig of the planetary gearbox system is acquired to be analysed by the novel method.

As described in Fig. 6 *(a)*, the test system consists of a motor, a two stage helical gearbox, a planetary gearbox, and a DC generator. Therefore, the vibration signal of the ball bearing from the complicated test system is contaminated seriously, which means the signal is interfered by the gear mesh, planetary motion and noise.

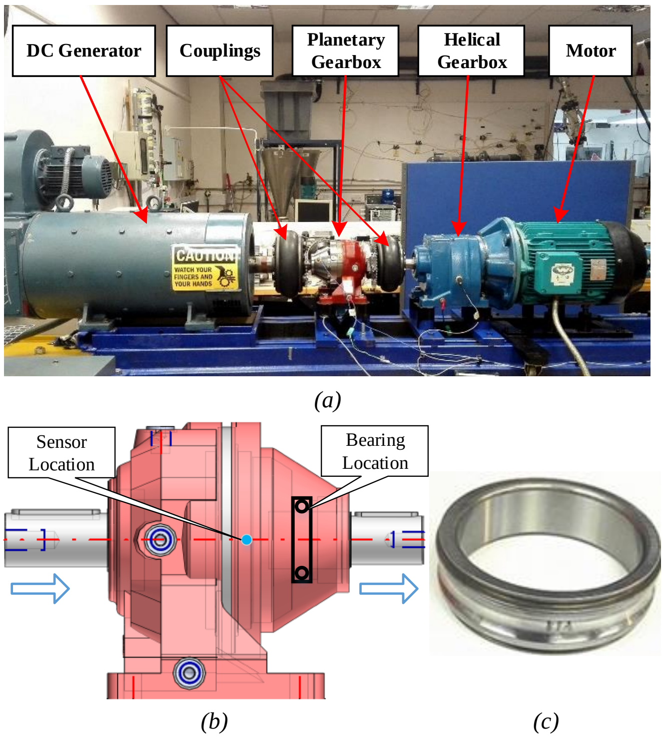

Fig. 6. Test system and the fault bearing

The maximum torque of planetary gearbox demonstrated in Fig. 6 *(b)* is 670 Nm and the maximum input speed is 388 rpm and maximum output speed is 2800 rpm. By way of addition, Fig. 6 *(c)* shows the inner ring fault of the SKF 6008 deep groove ball bearing and the specifications are listed in TABLE II.

TABLE II. SPECIFICATION OF THE BALL BEARING

Parameters	***Value***
Number of Balls	9
Ball Diameter	9.53 mm
Pitch Circle Diameter	46.4 mm
Contact Angle	0

In the experiment, the planetary gearbox operates at 75% of its full input speed and 25% of the full load. The vibration is measured by a generally piezoelectric accelerometer with a sensitivity of 31.9 mv/ms^{-2} and frequency response ranges from 1 Hz to 10,000 Hz. The vibration data were logged simultaneously for 30 seconds by a multiple-channel, high-speed, and 24-bit resolution data acquisition system at 96 kHz sampling rate. According to the encoder signal from the end of motor and the transmission ratio of two gearboxes, the shaft frequency is 9.5344Hz and the inner race fault frequency based on equation (4) is 65.6 Hz under the operating condition.

$$f_i = \frac{N_r}{2} f_r \left(1 + \frac{D_b}{D_c}\cos\varphi\right) \qquad (3)$$

where, N_r is number of balls, f_r is the shaft rotating frequency, D_b is the roller diameter, D_c is the pitch circle diameter, and φ is the contact angle.

As the bearing signal is collected by the data acquisition system, the fault detectors are applied to analyse the data sets. An optimal centre frequency 1339.3 Hz is determined by the system identification technique and then the demodulation analysis of the filter signal at 1339.3 Hz with the bandwidth of 1000Hz is carried out.

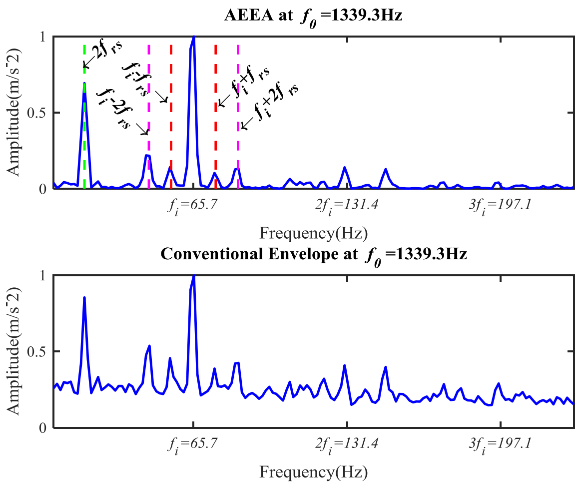

Fig. 7. Normalized spectra of AEEA

Fig. 7 illustrates the spectra of two modulation signals. In the first inset, the fault frequency 65.6 Hz and its harmonics can confirm the occurrence of localized defects on the inner ring. Besides, the second harmonic of the rotating frequency is captured in the spectrum of the auto-correlated envelope ensemble average and the sidebands of the fault frequency are also distinct. In the other hand, the average spectrum of the conventional envelope also detects the faults but the baseline is higher than the novel method, which denotes AEEA performs better to suppress noise. Furthermore, the second and third harmonic of the conventional method is difficult to distinguish from the noise.

In the practical application, AEEA conveys many details to promise the happening of local faults, which shows that the novel method is more robust in the field of condition monitoring.

V. CONCLUSIONS

System identification based condition monitoring is a promising technique and EAAC-SSI is a reliable and accurate method to automatically determine the optimal frequency bands for further demodulation analysis. Even though the impact signal is submerged by the high level noise, the system identification method is effective to extract the modal parameters. Furthermore, for the sake of the tolerance of fault frequency fluctuation and the noise reduction, auto-correlated envelope ensemble average is developed. In the simulation study, the novel fault detector resolves the contaminative signal at SNR of -26dB and in the slippage case, AEEA also successfully extracts the fault features and achieves the high noise reduction effect. The benchmark method, average spectrum of conventional envelope fails to indicate fault features in both two cases of simulation studies. Similarly, the robustness of the auto-correlated envelope ensemble average are analogous in the experimental signal processing with that in the simulation cases. To sum up, EAAC-SSI can be used to determine the optimal frequency bands. Furthermore, AEEA is accurate and reliable in the field of fault detection and it is robust to the high level noise and bearing system slippage.

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