Wayside Acoustic Fault Diagnosis of Train Wheelset Bearing Based on Improved Frequency Sparsity Bayesian Learning

YOU-LIANG ZHENG, YOU-WU WANG and YI-QING NI

ABSTRACT

Important train component like wheelset bearing endure severe mechanical loads and alternating stresses for an extended period when the train is in operation. The cracks due to bearing fatigue are often difficult to detect in time, which is the biggest hidden problem for train safety. The wayside acoustic detection of train bearing faults plays an important role in maintaining the safe operation of trains. However, the acoustic signals collected by the wayside microphones are usually complex, mixed with other irrelevant signals with strong background noise when in the condition monitoring of wheelset bearings. Moreover, when the train passes through the detection area at a certain speed, the microphone picks up the acoustic signal for a short time, which makes it difficult to obtain accurate fault signal characteristics. Trackside acoustics often uses microphone arrays to overcome the problem of short sampling time. To diagnose wheelset bearing faults more effectively with fewer microphones, this paper proposes a wayside acoustic fault diagnosis method based on improved sparsity Bayesian learning. Advanced sparse representation (SR)-based approaches usually include two primary stages: recovery of fault pulses in the time domain and frequency transformation of the estimated signal envelope. However, any inaccurate signal recovery in the time domain can introduce the problem of error accumulation in the subsequent frequency transform, which suffers from the disadvantage of low resolution, especially for short time sampled acoustic signal. Taking the limitations into consideration, a new algorithm has been developed by combining the group sparsity and periodic structure of fault pulses with variational Bayesian inference (VBI) technology. This advanced method effectively extracts the fault pulse signal, even in the presence of high noise levels, which leads to a significant enhancement in the fault detection performance. With the aid of this method, in conjunction with the Doppler distortion preprocessing correction algorithms, the proposed approach has been successfully applied to the diagnosis of faults in train trackside acoustic wheelset bearings. The experimental results show that the proposed method can achieve good performance in fault diagnosis compared with conventional analysis method, making it more effective to monitor wheelset bearing faults.

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INTRODUCTION

Currently, the lifecycle of key components such as rolling bearings in service on trains has entered the phase of high risk of failure. Strengthening the research of "train bearing condition monitoring and fault diagnosis" technology is of extremely urgent practical need and of great significance for ensuring the safe operation of urban rail transit and high-speed rail. Rolling bearings of high-speed trains have the characteristics of high speed, large load, and strong impact, and are one of the most critical functional components of trains. The train wheelset bearing's fault has historically been the principal cause of train failure [1]. Therefore, performing a fault diagnostic of train bearing is important. For the fault diagnosis of train bearings, a large amount of research has focused on some non-disassembled diagnostic methods, such as the oil measurement method [2-3], hot box method [4-5], on-board vibration signal analysis method [6-7], acoustic emission [8], and wayside acoustics [9]. The acoustic signal is generated by the reflection of mechanical waves in the propagation medium due to the vibration of the internal parts of the train. The acoustic signals triggered by train bearings range in frequency from 3 Hz to 40 kHz, and their intensity is often proportional to the acceleration signal in the same direction, so they are sensitive enough to support the identification of minor fatigue cracks. Comparing different types of detection methods, the acoustic signals have the characteristics of non-contact, easy to measure, simple equipment, etc. Currently, there is relatively little research on the use of acoustic signals for train bearing fault diagnosis, in contrast to the more commonly used vibration signal analysis. There are three challenging research areas in the study of wayside acoustic fault diagnosis for train bearings, namely, dealing with multiple sources, handling strong noise, and managing steep distortion. Numerous researchers have studied methods for extracting bearing fault signals using vibration signals [10-12]. Recently, the sparse signal recovery has emerged as a highly effective technique for bearing fault diagnosis, sparking renewed interest in the field. For example, Wang et al. [13] proposed reweighted dual sparse regularization method which is combined framework with an additional l_2-norm regularization. Zhou et al [14] developed an algorithm that utilizes an overcomplete dictionary of Attenuated Cosines (AC) basis, specifically tailored to closely match the waveforms of bearing faults. While the current sparse signal recovery techniques for bearing fault diagnosis can deliver exceptional results, their reliance on the l_1-norm as an approximation of l_0-norm can cause a deterioration in algorithm performance. Taking the drawbacks into account, Dai et al [15] suggested a algorithm that combines group sparsity and periodic structure of fault pulses with variational Bayesian inference (VBI) technology. This method helps extract fault pulse signal accurately even in a noisy environment, which leads to a remarkable improvement in fault detection performance. Based on this method combined with the Doppler distortion preprocessing correction algorithms, the proposed method is applied to the fault diagnosis of train trackside acoustic wheelset bearings, which can effectively diagnose the faults of train wheelset bearings.

PROBLEM STATEMENT AND METHOD

The observed acoustic signals can be described following Equation:

$$\boldsymbol{y}\,(\boldsymbol{t}) = \boldsymbol{s}(\boldsymbol{t}) + \boldsymbol{N}(\boldsymbol{t}) \tag{1}$$

where $\boldsymbol{s}(\boldsymbol{t})$ represents the fault pulse signal, and $\boldsymbol{N}(\boldsymbol{t})$ represents the strong noise background signal. The purpose of fault diagnosis of the train wheelset bearings is to extract the noise-free pulse signal $\boldsymbol{s}(\boldsymbol{t})$ from the acoustic signal $\boldsymbol{y}(\boldsymbol{t})$ collected by the trackside. Note that $\boldsymbol{s}(\boldsymbol{t})$ has a periodic or quasi-periodic group sparse structure. Assume that P is the cycle of $\boldsymbol{s}(\boldsymbol{t})$ and f_s is the sampling frequency, so the number of samples R in one cycle is as follow:

$$R = f_s P \tag{2}$$

The P is known when the train bearing size is determined, and when the train running speed is also determined. The following binary vector p can be introduced to represent the group sparsity of each period.

$$\boldsymbol{p} = \left[\underbrace{1,1,\dots,1}_{N_1}, \underbrace{0,0,\dots,0}_{N_0}\right]^{\mathrm{T}} \tag{3}$$

If each periodic fault impulse appears in a block of size N_1 and is followed by $N_0 = R - N_1$ zeros, G periods are then assembled into a larger group to enforce the periodic group-sparsity of $\boldsymbol{s}(\boldsymbol{t})$. Namely,

$$\mathbf{b} = [\underbrace{\mathbf{p}^{\mathrm{T}}, \mathbf{p}^{\mathrm{T}}, \dots, \mathbf{p}^{\mathrm{T}}}_{G}]^{\mathrm{T}} \tag{4}$$

where the nearby G periods share the same sparsity structure, and the optimization problem can be formulated as follows:

$$\min_{x} \quad \frac{1}{2} \| y(t) - s(t) \|_2^2 + \lambda\Big(\sum_i \phi(\| b \odot \vec{s}_i \|_2) + \mu N N_1 \psi(s)\Big) \tag{5}$$

where $\vec{s}_i = [s_i, s_{i+1}, \dots, s_{i+RG-1}]^T$, and $\odot$ denotes Hadamard product, μ is another regularization parameter, $\phi\,(\cdot)$ is a sparsity penalty function. Then a P-GSL algorithm for bearing fault diagnosis is proposed using the SBL framework. Finally, the Bayesian Formulation and VBI-Based Inference can be calculated [15].

EXPERIMENTS AND RESULTS

This study collected a large amount of acoustic signal data under various operating conditions and failure locations of train wheelset bearings at different speeds, as shown in Figure 1. During the acoustic signal acquisition process of the laboratory wheelset bearings, the microphone was positioned as close as possible to the wheelset bearing seat to minimize sound signal attenuation. The recorded audio was used to simulate the sound emitted by a train wheelset bearing when it fails during on-site testing, as known that trains with known bearing issues cannot operate for safety reasons. Experiment 1 involved simulating the acoustic testing of bearing faults on a roadside as shown in Figure 2. A Bluetooth speaker was mounted on the door of the car, and when the driver operated the car at a specified set of speeds, the Bluetooth speaker was connected to the computer via Bluetooth and played the bearing-damage audio recorded in the laboratory, with the corresponding rotating speed. Figure 3 shows the time domain diagram of data collected by roadside microphone array under the condition of a car running at a speed of 30km/h. At this time, the fault audio played by the speaker is collected by the laboratory wheelset bearing outer race fault at a speed of 175RPM, the corresponding fault frequency is 21.2Hz. Figure 4 shows the effectiveness of the periodic group sparse learning method in the diagnosis results. Compared with other methods, it can clearly diagnose the outer ring fault of the wheel set bearing, and the second harmonic of the outer race fault frequency and high subharmonics are evident.

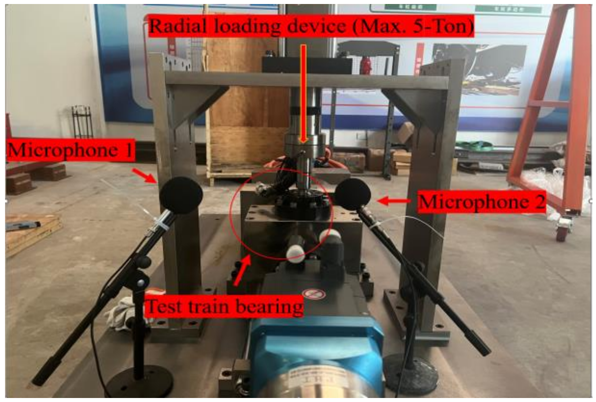

Figure 1. Acoustic signals acquisition of train bearing testbed.

Figure 2. Field test of the simulated wayside acoustic train bearing fault diagnosis.

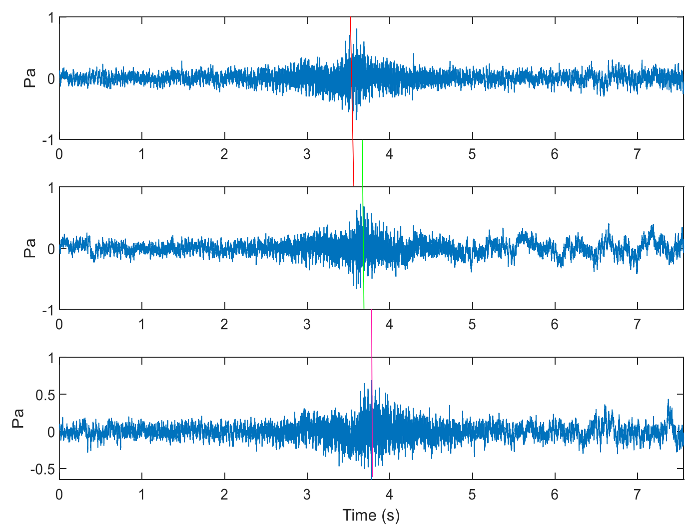

Figure 3. Time domain diagram of data collected by roadside microphone array

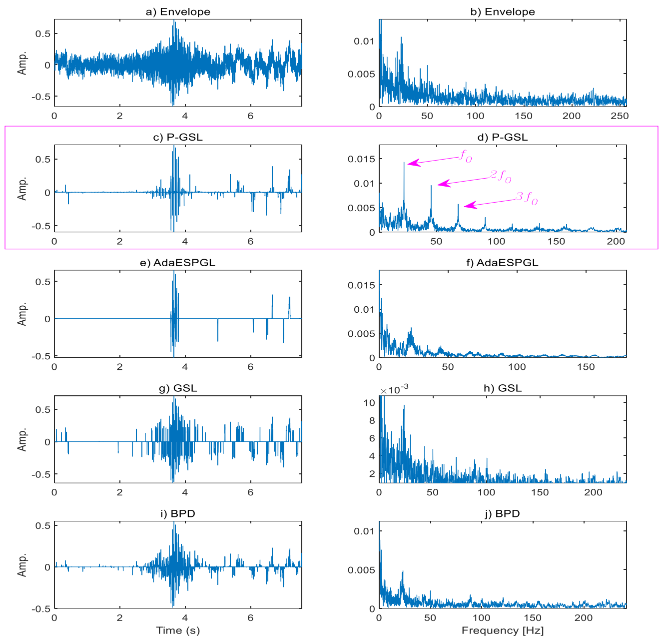

Figure 4. Fault diagnosis results of different methods after calibration (a & b) envelope analysis method. (c & d) Periodic group sparse learning. (e &f) Enhanced sparse periodic lasso. (g & h) Group sparse learning method. (I & J) base pursuit decomposition method

Experiment 2 involved field test of the trackside acoustic train bearing fault diagnosis as show in Figure 5. Figure 6 shows the damaged audio of the outer ring when the speaker is playing while the subway train is hovering. The acoustic signals collected by the six microphones beside the track. When the train passes through the trackside microphone array at a constant speed, the bearing damage signal collected by each microphone is very short-lived, because the acoustic signal of the bearing fault gradually weakens after the train passes by, so to further compare the effectiveness of the algorithm 1s data of the above-mentioned collected acoustic signal is intercepted, with a total of 20k samples. The comparison of the fault diagnosis results of the 1s acoustic data of the wheelset bearing is shown in Figure 7. It can be clearly seen that the periodic group sparse learning method is more clear than other algorithms in diagnosis results, and high-order harmonic components can also be clearly seen, so the P-GSL method is effective in the application of trackside acoustic fault diagnosis.

Figure 5. Field test of the trackside acoustic train bearing fault diagnosis.

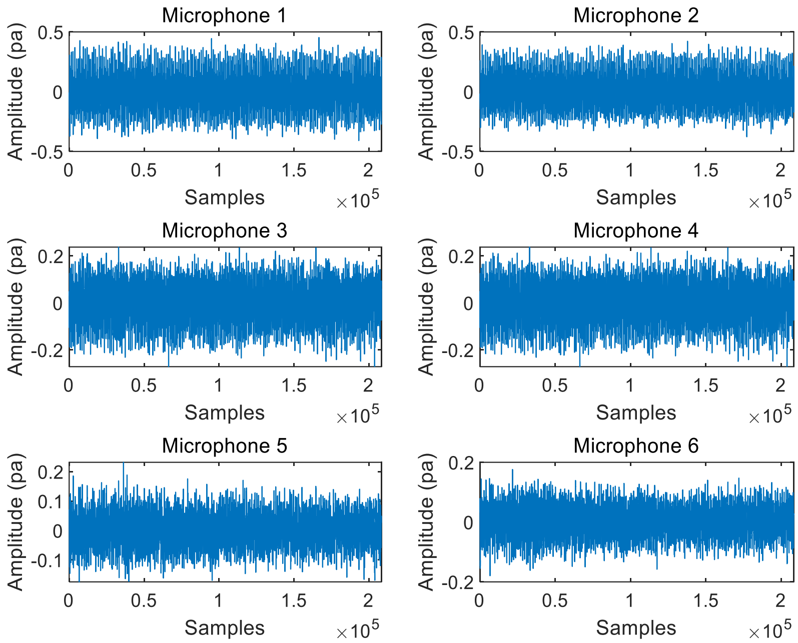

Figure 6. Time domain diagram of data collected by trackside microphone array

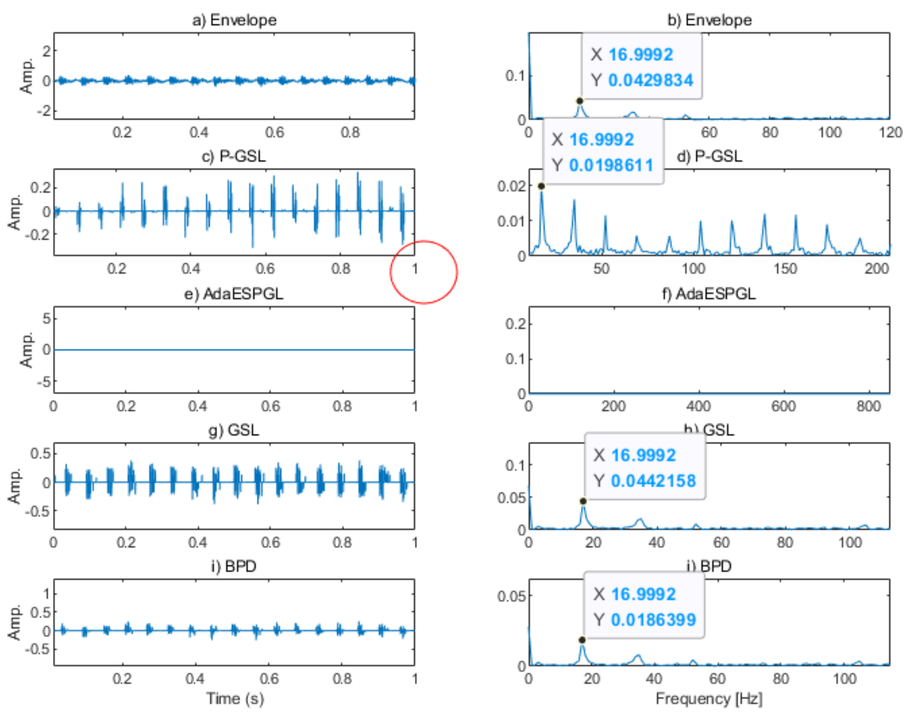

Figure 7. Fault diagnosis results of different methods after calibration (a & b) envelope analysis method. (c & d) Periodic group sparse learning. (e &f) Enhanced sparse periodic lasso. (g & h) Group sparse learning method. (I & J) base pursuit decomposition method

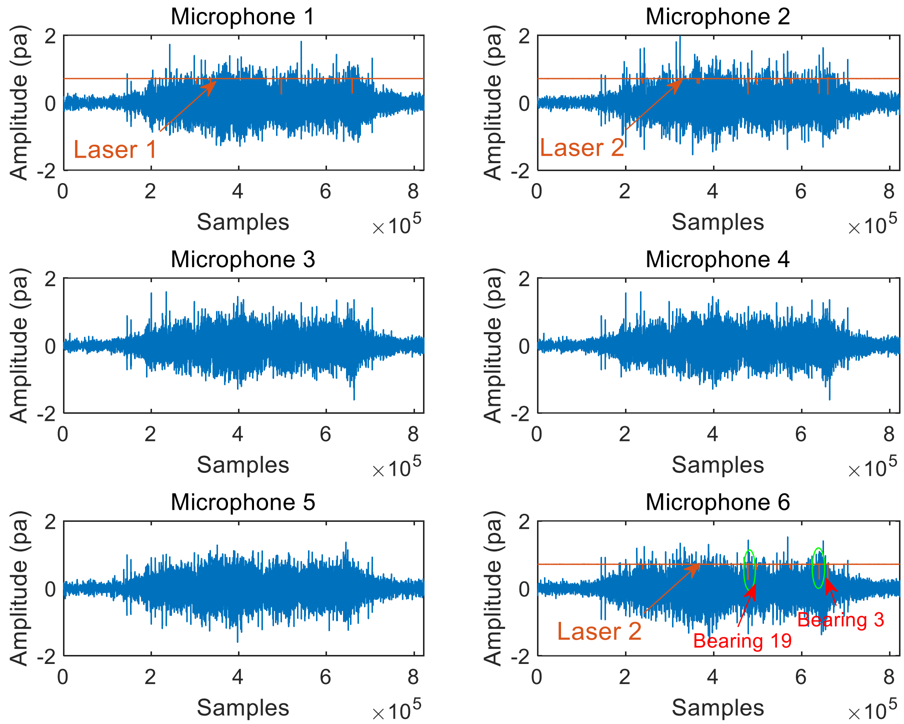

Figure 8. Time domain diagram of data collected by trackside microphone array and lasers

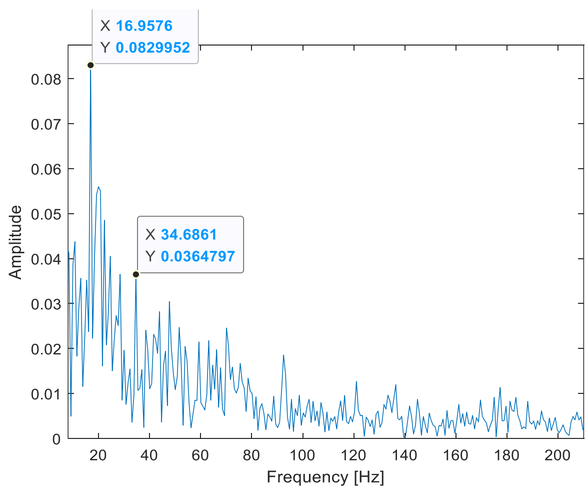

Figure 9. Fault diagnosis results of outer race of wheelset bearing based on trackside acoustics at 20km/h speed of Metro train

To further verify the effectiveness of this diagnostic algorithm, Figure 8 shows the measured data of the trackside microphone array under the condition of a subway train at a speed of 20km/h. The infrared laser shown in the figure is used to locate the position of the wheel set bearing. Figure 9 shows the fault diagnosis results of the outer race of the trackside acoustic wheelset bearing under the speed of 20km/speed of the subway train. The fault frequency and the second harmonic of the outer ring are clearly seen, and the fault frequency value currently matches the calculated frequency value, once again verifying the effectiveness of the algorithm application.

CONCLUSION

Prior to conducting the bearing fault diagnosis, first to perform Doppler correction as a data preprocessing step on the acoustic signals obtained through trackside acoustics. The periodic group sparse learning method has proven to be effective for diagnosing faults in wayside acoustics.

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REFERENCES

1. CHOE, H. C., WAN, Y. & CHAN, A. K. Neural pattern identification of railroad wheel-bearing faults from audible acoustic signals: comparison of FFT, CWT, and DWT features. Wavelet applications IV, 1997. SPIE, 480-496.
2. TOPóR, T., DERKOWSKI, A., KUILA, U., FISCHER, T. B. & MCCARTY, D. K. 2016. Dual liquid porosimetry: A porosity measurement technique for oil-and gas-bearing shales. Fuel, 183, 537-549.
3. ZHANG, P., LI, J., LU, S., XUE, H., ZHANG, J. & YANG, J. 2017. A precise porosity measurement method for oil-bearing micro/nano porous shales using low-field nuclear magnetic resonance (LF-NMR). Journal of Nanoscience and Nanotechnology, 17, 6827-6835.
4. MEALER, A., TARAWNEH, C. & CROWN, S. Radiative heat transfer analysis of railroad bearings for wayside hot-box detector optimization. ASME/IEEE Joint Rail Conference, 2017. American Society of Mechanical Engineers, V001T02A008.
5. TARAWNEH, C., ARANDA, J. A., HERNANDEZ, V. V. & RAMIREZ, C. J. An analysis of the efficacy of wayside hot-box detector data. ASME/IEEE Joint Rail Conference, 2018. American Society of Mechanical Engineers, V001T02A012.
6. MENDEL, E., MARIANO, L., DRAGO, I., LOUREIRO, S., RAUBER, T., VAREJAO, F. & BATISTA, R. Automatic bearing fault pattern recognition using vibration signal analysis. 2008 IEEE International Symposium on Industrial Electronics, 2008. IEEE, 955-960.
7. YAN, R. & GAO, R. X. 2009. Multi-scale enveloping spectrogram for vibration analysis in bearing defect diagnosis. Tribology International, 42, 293-302.
8. MORHAIN, A. & MBA, D. 2003. Bearing defect diagnosis and acoustic emission. Proceedings of the Institution of Mechanical Engineers, Part J: Journal of Engineering Tribology, 217, 257-272.
9. ZHANG, S., HE, Q., OUYANG, K. & XIONG, W. 2018b. Multi-bearing weak defect detection for wayside acoustic diagnosis based on a time-varying spatial filtering rearrangement. Mechanical Systems and Signal Processing, 100, 224-241.
10. ZHENG, Z., SONG, D., XU, X. & LEI, L. 2020. A fault diagnosis method of bogie axle box bearing based on spectrum whitening demodulation. Sensors, 20, 7155.
11. Guo, J., Zhen, D., Li, H., Shi, Z., Gu, F., & Ball, A. D. (2019). Fault feature extraction for rolling element bearing diagnosis based on a multi-stage noise reduction method. Measurement, 139, 226-235.
12. Li, Y., Liang, X., Xu, M., & Huang, W. (2017). Early fault feature extraction of rolling bearing based on ICD and tunable Q-factor wavelet transform. Mechanical Systems and Signal Processing, 86, 204-223.
13. Wang, L., Ma, S., & Han, Q. (2020). Reweighted dual sparse regularization and convex optimization for bearing fault diagnosis. IEEE Transactions on Instrumentation and Measurement, 70, 1-9.
14. Zhou, H., Li, H., Liu, T., & Chen, Q. (2020). A weak fault feature extraction of rolling element bearing based on attenuated cosine dictionaries and sparse feature sign search. ISA transactions, 97, 143-154.
15. Dai, J., & So, H. C. (2021). Group-sparsity learning approach for bearing fault diagnosis. IEEE Transactions on Industrial Informatics, 18(7), 4566-4576.