Bearing Fault Diagnosis Based On Reinforcement Learning And Kurtosis

Wenxin Dai, Zhenling Mo, Chong Luo, Jing Jiang, Qiang Miao*
Center of Aerospace Information Processing and Application, School of Aeronautics and Astronautics, Sichuan University, Chengdu, Sichuan 610065, China
Email: daiwenxin@stu.scu.edu.cn

***Abstract*—Vibration signal of rolling element bearing is usually much complicated due to the presence of random slipping of rolling element and a lot of noise. Therefore, it is often difficult to extract fault features from the collected signal. In classic bearing fault diagnosis, it is necessary to use a bandpass filter to process the original vibration signal, and use demodulation techniques to obtain fault features. The kurtosis of vibration signal is sensitive to fault information, which makes it a good indicator. In this paper, a reinforcement learning system with kurtosis as an index is constructed to train a bandpass filter to adjust its upper and lower cutoff frequencies. Thereby, the bandpass filter can select the frequency band with the largest signal to noise ratio. Then, demodulation of the filtered signal is performed so as to diagnose the fault of rolling bearings. In order to verify the effectiveness of the proposed method, vibration signal collected from rolling element bearing with an inner race fault is studied. The comparison with fast kurtogram method indicated that the proposed reinforcement learning approach has great potential for diagnosing bearing faults.**

***Keywords*—Fault diagnosis, rolling element bearing, kurtosis, reinforcement learning, bandpass filter.**

I. Introduction

Rolling element bearing has widespread applications in mechanical systems. Bearing is easily influenced by lubrication condition, corrosion, overload, and foreign body invasion, resulting in many faults, such as rolling element fault, cage fault, inner ring fault, and outer ring fault. Presence of bearing fault may cause mechanical failure, thus requiring expensive maintenance costs [1]. Therefore, it is important to monitor health condition of bearing so as to timely diagnose faults. Vibration signal of rolling bearing contains a lot of information of faults [2]. When a local fault occurs on a bearing, it produces periodic impulsive signal. However, presence of noise may greatly affect extraction of fault feature.

Thus, it is significant to choose an appropriate indicator for selecting optimal band in oeder to effectively extract fault features. Kurtosis, as a statistical prameter indicating departure from normality, can therefore measure shocks in signal. Here, smoothness index [3] and Gini index [4] also has a widespread application in fault detection. Since the kurtosis is sensitive to impulsiveness of vibration signal, it is selected as the index in this paper. Based on kurtosis, Antoni proposed the spectral kurtosis as an useful tool for fault detection [5]. Antoni also put forward a new approch called kurtogram for fault diagnosis of rotating machinery [6], but it is not efficient enough to apply in on-line industrial applications. Later, the fast kurtogram was proposed to enhance the capability of kurtogram [7]. However, the fast kurtogram can be influenced by outliers [4], [8] and it also lacks fexibility since its filter bands are fixed. To address these problems, this paper aims to propose an artificial intelligence algorithm with a different calculation of kurtosis to diagnose bearing fault.

Recently, reinforcement learning attracts much attentions thanks to Alpha Go and OpenAI Five appearing in public eyes. As it is known, reinforcement learning shows excellent performance on solving sequential decision problems. In this work, the author put forward a new diagnosis method, which combines reinforcement learning algorithm and kurtosis to diagnose bearing fault. By comparing with fast kurtogram method, the proposed method can select the better upper and lower cutoff frequencies of the bandpass filter,which can be regared as a promissing tool to bearing fault diagnosis.

The rest of this paper is organized as follows. A brief explanation of the theoretical background of reinforcement learning and kurtosis are given in Section II. Section III provides details of the method offered in this paper. A case study is presented in Section IV. Finally, conclusions and outlooks are provided in Section V.

II. Theoretical Background.

A. *Kurtosis*

Kurtosis is a statistical parameter, which is proposed by Dyer [9] to evaluate damage level of rolling element bearings. When a rolling elememnt bearing is running with no faults, its distribution of the collected vibration signal is close to normal distribution. If there is a fault on bearing component, the probability density of impulses would increase, which results in the deviation from normal distribution. Consequently, the kurtosis would also increase. The greater value of kurtosis is, the more serious the fault becomes. Kurtosis is also used in prognostic and condition monitoring of rolling bearing.

According to Borghesani et al. [10], the vibration signal $x_f[n]$ can be filtered by a band-pass filter $f_{l,h}[n]$ with non-dimensional pass-band $l \le k < h$ from the measured signal $x[n]$ through convolution as follows.

$$x_{l,h}[n] = x[n] \otimes f_{l,h}[n] \tag{1}$$

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The analytic signal $\tilde{x}[n]$ can be calculated as follows:

$$\tilde{x}_{l,h}[n] = x_{l,h}[n] + j \bullet Hilbert\{x_{l,h}[n]\} \quad (2)$$

The kurtosis $k_{l,h}$ of this signal is the fourth central moment m_4 divided by the square of the variance m_2 of $\tilde{x}_{l,h}[n]$:

$$k_{l,h} = \frac{m_4\{\tilde{x}_{l,h}[n]\}}{(m_2\{\tilde{x}_{l,h}[n]\})^2} \quad (3)$$

The above calculation of kurtosis is based on envelope signal. However, the outlier of envelope signal may have impact on kurtosis. This paper calculates the kurtosis of the envelope spectrum, i.e., $ESk_{l,h}$, so as to reduce the influence of outliers. Taking the Fourier transform of $\tilde{x}_{l,h}[n]$ to get $f[n]$, and the $ESk_{l,h}$ can be calculated as follows:

$$ESk_{l,h} = \frac{m_4\{f[n]\}}{(m_2\{f[n]\})^2} \quad (4)$$

B. *Reinforcement Learning*

Reinforcement learning, as one of the branches of machine learning, has extensive applications in a lot of fields, such as intelligent control, intelligent prediction and analysis. In reinforcement learning, the learning agent only focuses on one goal, i.e., maximizing the reward that the agent received [11]. It is different from unsupervised learning and supervised learning. Supervised learning is to learn from the data that has corresponding labels to build predictive models [12], and unsupervised learning is to learn based on the unlabeled data so as to do classification on the data and cluster the data [13]. Reinforcement learning requires no data labels, and it does not need to find hidden common property in the data. Reinforcement learning agent just has to interact with the environment to explore how to obtain rewards. Thus, after training the agent, it can find an optimal action to get the maximum reward value by interacting with the environment.

In addition to agent and environment, a reinforcement learning system needs the other four elements -- policy, reward, value function, and environmental model. The policy is the most important part of a reinforcement learning agent, and it defines the way of agent action. Reward signal gives the agent an explicit objective to maximize the reward, which is the environment feedback to the agent after the agent makes an action in each iteration. Reward tells the agent what is good at this moment, whereas value function tells the agent what is good in a long period. Environmental model is optional in reinforcement learning and if a state and an action is given to the model, it can infer the state and reward in the next moment.

According to three factors, namely, state, action, and reward, the process of reinforcement learning agent interacting with the environment usually can be illustrated by using a framework of Markov decision processes. Therefore, it is not difficult to find that reinforcement learning is a machine learning method by interacting with the environment with incomplete models to deal with sequential decision problem.

III. PROPOSED METHOD

In practice, characterisitc frequencies of bearing fault are usually masked by noise and other interfering frequencies. Therefore, selecting an appropriate frequency band that can give a clear picture of characteristic fault frequencies after demodulation is very important. This problem can be regarded as making a decision of choosing appropriate cutoff frequencies of the optimal frequency band. As we know, reinforcement learning shows good performance in making the optimal decision, which can be utilized to solve the above-metioned problem. Based on the idea, this section presents a reinforcement learning approch for bearing fault diagnosis.

In the first step, a bandpass filter is chosen to filter the original vibration signal, and the upper cutoff frequency and the lower cutoff frequency can be adjusted in order to build an optimal frequency band. In this process, the behavior of adjusting the cutoff frequencies can be defined as an action with two dimensions. Then, the bandpass filter can be regarded as the agent. Meanwhile, the environment of reinforcement learning can be set to the spectrum of the vibration signal. Next, the framework of reinforcement learning can be built as Figure 1. In addition, there are some constraints for the bandpass filter. First, the minimum bandwidth of the bandpass filter should ensure observation of several bearing characterisitc frequencies. Second, the lower cutoff frequency should be below upper cutoff frequency. Third, due to attenuation of bandpass filer, small areas near the spectrum edges are not considered.

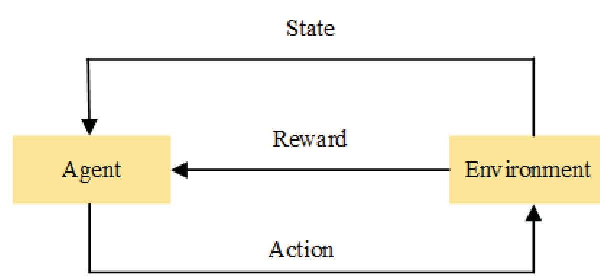


Figure 1 The framework of reinforcement.

The position of the bandpass filter corresponds to the state. Firstly, the agent obtains the temporal state from the environment. Secondly, in light of the state, the agent uses a reinforcement learning algorithm to make a decision on action selection. Thirdly, the action interacts with the environment to generate a reward and a new state, and these parameters become the feedback for the agent. After that, the agent uses the algorithm to make the next action based on the feedback. Then the reinforcement learning system is going to do loop iteration.

In the second step, an intelligent agent needs to be established. Adjusting the cutoff frequency of the bandpass filter, which comes down to control the position of the bandpass filter, and this process can be regarded as controling a slider to move left and right in the specctrum. Therefore, the policy gradient algorithm is suitable for this situation.

Policy gradient is a strategy search method which parameterizes the policy to be $\pi_\theta(s,a)$. In detail, the policy is represented by a parametric linear function or nonlinear function (such as Neural Networks). According to the expected reward associated with policy parameters, the policy is updated to find the best parameter by maximizing the goal, i.e., cumulative reward expectations, of reinforcement learning [14]. The specific update process of policy gradient algorithm is as follows:

Policy Gradient Algorithm
function REINFORCE
Initialize θ arbitrarily
for each episode $\{s_1,a_1,r_2,...,s_{T-1},a_{T-1},r_T\} \sim \pi_\theta$ do
for t =1 to T-1 do
$\theta \leftarrow \theta + \alpha \nabla_\theta \log \pi_\theta(s_t,a_t) v_t$
end for
end for
return θ
end function

In the update process, s_{T-1} is the state at time $T-1$, a_{T-1} is the action at time $T-1$, r_T is the reward at time T, θ is the weight of neural network, which is used to approximate state-action value function and state value function. π_θ is the parameterized policy. α is the learning rate. $\log \pi_\theta(s_t,a_t)$ is used to transform the policy into probability; then take the partial derivative with respect to the probability to calculate the gradient; v_t is calculated by using policy gradient theorem and the stochastic gradient ascent algorithm.

In the third step, each time an action is generated, build a corresponding bandpass filter to filter the original vibration signal; next, ues the Hilbert transform to the filtered signal and calculate the kurtosis according to the envelope spectrum of the filtered signal. The reward of each action can be set as $ESk_{l,h}$. The reinforcement learning system will converge after iterating a certain number of times, and the $ESk_{l,h}$ would be the maximum.

IV. CASE STUDY

Figure 2 (a) shows the test rig, and the real data was collected from the bearing with an inner race fault (shown in figure 2 (b)). The data is applyed to validate that the proposed method is effective.

A. *Data description*

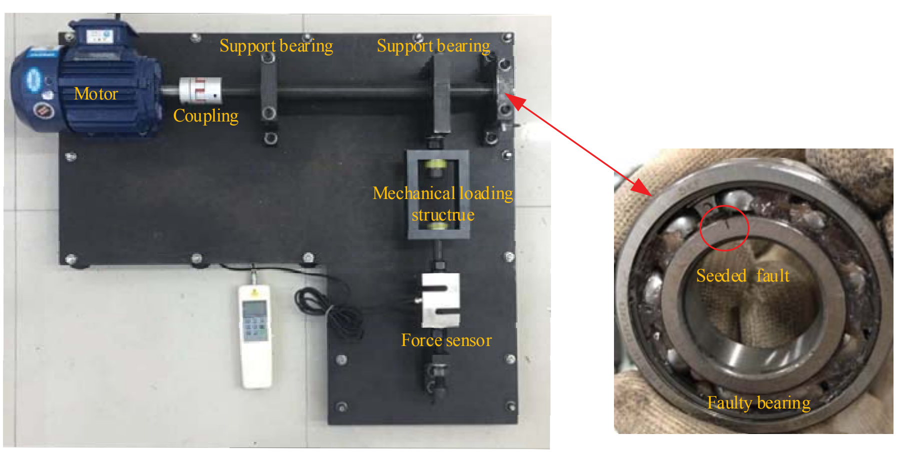
The bearing type is 6205-2RS SKF with the seeded fault on the inner race. The fault is generated by using wire-electrode cutting with wire width equaling to 0.2 mm. During the data collection, the speed of the motor kept at 1046 rpm (revolution-per-minute). A force of 1 kN from the mechanical loading structure was loaded on the bearing. The NI acquisition unit (NI PXI-4462) was used, and an accelerometer was installed on the bearing pedestal to gather data. In the experiment, the sampling rate is 10 kHz, and 102400 samples are used in reinforcement learning system. Table 1 provides the detailed information of the bearing. Calculating the FCF (fault charecter frequency) of inner race is equivalent to calculating the BPFI (ballpass frequency, inner race) which is equal to 94.6 Hz and can be obtained by following equation [15].

$$BPFI = \frac{nf_r}{2}\left\{1+\frac{d}{D}\cos\phi\right\} \tag{5}$$

where f_r is the shaft speed, n is the number of rolling elements, ϕ is the contact angle, d is the ball diameter, and D is the pitch diameter.

TABLE I. INFORMATION OF INNER RACE FAULT BEARIN

Bearing type	6205-2RS SKF
Ball number	9
Ball diameter (mm)	7.938
Pitch diameter (mm)	37.5
Contact angle ($^\circ$)	0



(a) (b)

Figure 2 Test rig of inner race fault bearing: (a) the test rig, (b)the rolling bearing with the fault in inner race.

B. *Data Analysis*

Figure 3 shows the original vibration signal. Due to the interference, the inner race fault impulses may be difficult to detect. Then, use the vibration signal as the input of the reinforcement learning system so as to diagnose the inner race fault.

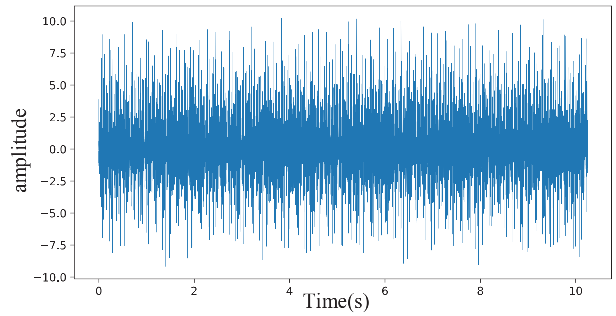


Figure 3 The original vibration signal on the time domain.

The relationship between the number of iterations and the $ESk_{l,h}$ can be seen in Figure 4. It is very clear that the reinforcement learning system almost converges after five iterations, and the $ESk_{l,h}$ value is around 38 in the case of convergence. Next, according to the largest $ESk_{l,h}$, the optimal frequency band is obtained.

In this case study, the largest $ESk_{l,h}$ is equal to 38.54, and the corresponding upper and lower cutoff frequencies are 4311.79 Hz and 2148.03 Hz, respectively. After that, use the bandpass filter to filter the original vibration signal, and Hilbert transform is applied to the filtered signal. Then, calculate the envelope of the transformed signal. Finally, take the Fourier transform of the envelope, and Figure 5 shows the result of transform. The fault characteristic frequency and its several harmonics can be seen clearly. Thus, the result proves the presence of the fault in the rolling bearing.

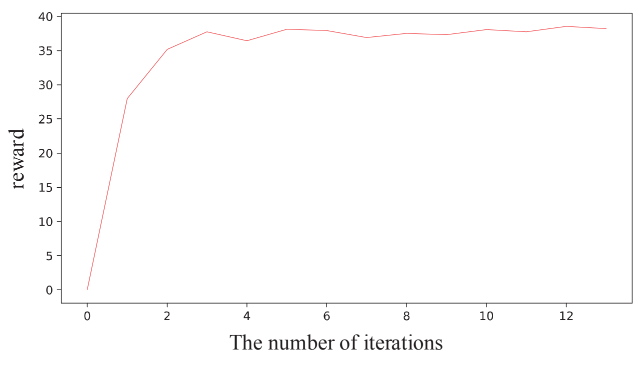


Figure 4 The change of the maximum $ESk_{l,h}$ during training.

Meanwhile, the fast kurtogram is also applied to process same vibration signal, and the result is shown in Figure 6 and Figure7. It is known from Figure 7 that the fast kurtogram selects the optimal frequency band, which center band is 208.33Hz and bandwidth is 104.16Hz. However, according to Figure 6, due to the existence of a lot of noises, the fault characteristic frequency is diffilutc to be seen in this frequency band.

Through such comparison, it is clear that the proposed reinforcement learning approach shows better performance than fast kurtogram method.

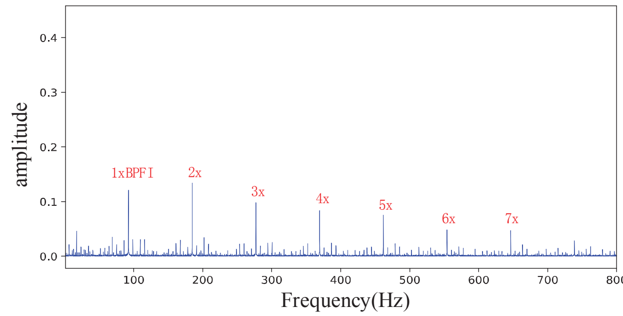


Figure 5 The Fourier transform of envelope signal obtained by the proposed method.

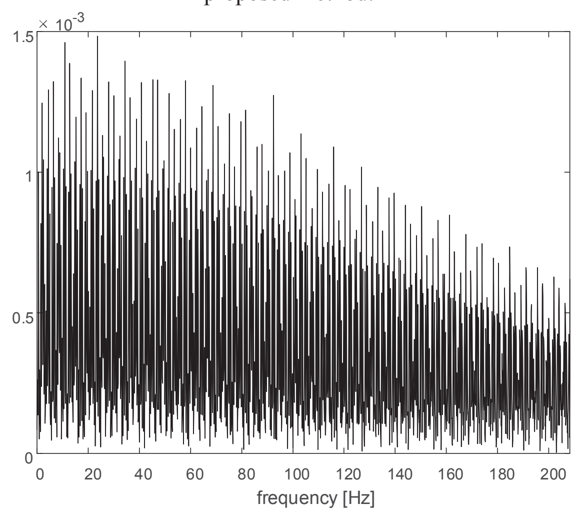


Figure 6 Envelope spectrum provided by fast Kurtogram.

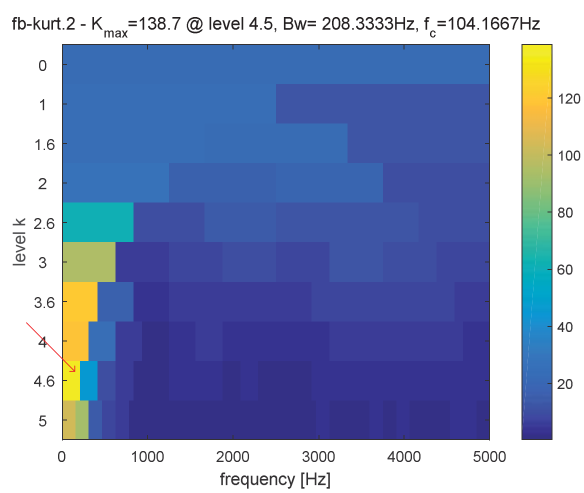


Figure 7 Fast Kurtogram of the signal of Figure 3

V. Conclusion

In this work, a fault diagnosis method based on reinforcement learning and kurtosis is put forward to realize band-pass filter design. The core of this approach is to apply a reinforcement learning algorithm to train the bandpass filter, so as to find the frequency band with the richest fault information. The vibration signal of a rolling bearing with inner race fault is applied to show the effectiveness of this method. The comparison with fast kurtogram method indicates that the method of this paper can efficiently and effectively get the frequency band with apparent fault frequencies.

In the future work, more powerful reinforcement learning algorithms, such as asynchronous advantage actor-critic and deep deterministic policy gradient, may be utilized in the similar way for mechanical fault diagnosis.

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