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ONLINE PHM SYSTEM FOR BEARINGS BASED ON TIME-FREQUENCY ANALYSIS AND CNN TRANSFER LEARNING

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ABSTRACT

Bearings are important transmission components for rotating machinery, and their remaining life prediction plays a crucial role in equipment maintenance decisions. In this paper, the gearbox of crane running online is the research target. Because the bearing accounts for a high proportion of the historical machine failure, taking the bearing as an example to detail the overall framework and algorithm details for monitoring, diagnosis, and prognosis. The current bottlenecks in bearing failure prediction are: (1) The bearing health status and failure mode are uncertain during operation. (2) The value density of data is low and cannot support the training of neural networks. (3) Lack of accurate failure data for economic and security reasons. (4) Compared with the run-to-failure experiment, the bearings of different types of gearboxes are different, and the working conditions are quite different. Even for the same type of bearing, according to a large number of data, the life of rolling bearings is presented as a discrete distribution, and the prediction model (curve) is difficult to transfer directly. Therefore, the identification of the degraded state and early failure of in-service bearings is significant for accurately predicting the remaining life. In contrast, bearing datasets obtained by these run-to-failure experiments can accurately obtain the monitoring data of the bearing from health to damage throughout the life cycle, to facilitate the division of the recession phase, training the classifier. This paper proposes a universal transfer learning analysis scheme for online PHM system of rotating machinery: Time-frequency analysis is used to evaluate the performance degradation of the bearing state, determine the time of the early failure, and divide the health and damage data. Transfer the CNN classifier originally trained by the experimental data to online data, which helps the abnormal detection of the online equipment, and finally the life prediction is completed by the piecewise prediction model.

Keywords: CNN, Transfer learning, Bearing, PHM, Online system, Time-frequency analysis

1 INTRODUCTION

In order to solve the bottleneck problem of PHM in-service operation, this paper takes the gearbox as an example to design the overall framework of online monitoring, diagnosis and prediction based on migration learning as follows:

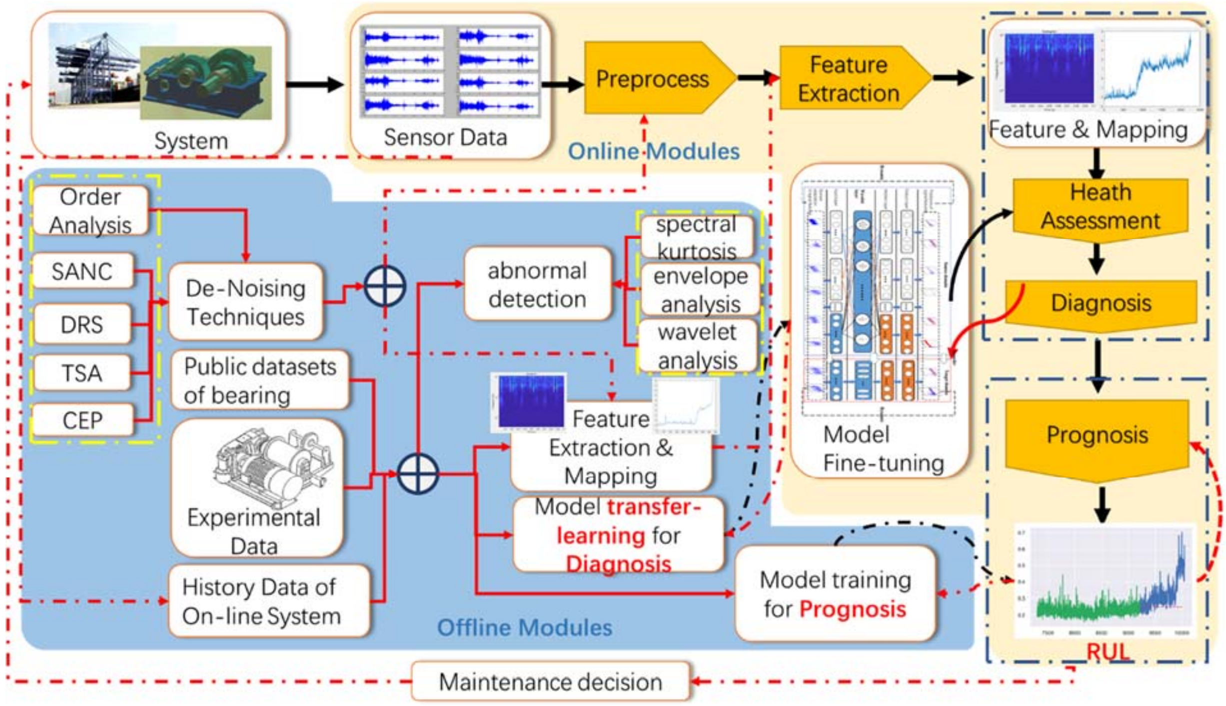

Figure 9: Framework for monitoring, diagnosis and prediction of in-service equipment

The main analytical processing flow of data includes: (1) On-line operation of gearbox monitoring. This paper mainly analyses the condition of the equipment by monitoring the vibration signal of the bearing cover of the four-stage gearbox. (2) Pre-processing. Complete signal denoising and separation and enhancement of useful signals, Randall (2011) Introduced an effective diagnostic procedure for bearing diagnosis [1]. The main algorithm library included in the offline system: order analysis, self-adaptive noise cancellation (SANC), deterministic random separation (DRS), Time synchronous averaging (TSA), cepstral editing procedure (CEP), etc., subsequent chapters on algorithms and effects Make a detailed introduction. (3) Feature extraction. It includes time domain features of the signal, frequency domain features, and time-frequency domain features. (4) Health Assessment, the principal component analysis (PCA) is used to reduce the dimension of the feature, and the principal component is used to characterize the degree of decline of the bearing state. Look for the time point of the early failure, and use the abnormal detection algorithm such as spectral kurtosis, envelope analysis, wavelet analysis to divide the health and fault bearing data. (5) Diagnosis. Through the CNN migration learning, the CNN classifier trained by the experimental data is migrated to the online running device for fault diagnosis, and the online system automatically distinguishes the bearing health and fault state. (6) Prognosis. The segmentation prediction model is trained according to the degree of bearing degradation to predict the remaining life. (7) Maintenance decision. Schedule maintenance time based on condition monitoring and life prediction.

The data set used to train the algorithm and model includes: two sets of international open bearing data sets provided by IEEE PHM 2012 Data Challenge [2] and Intelligent Maintenance Systems (IMS) as the source domain of migration learning, and online monitoring of gearbox vibration data as The target domain for migration learning.

2 PREPROCESSING

This article mainly introduces two common and effective methods and treatments in bearing diagnostic pre-processing: Order Analysis and self-adaptive noise cancellation. In addition to deterministic random separation (DRS), Time synchronous averaging (TSA), cepstral Editing procedure (CEP), wavelet denoising, Empirical Mode Decomposition (EMD), etc., the detailed algorithm and role can reference [3].

2.1 Order analysis

For rotating machine, the response of vibration or noise changes as the speed changes. Order Analysis is used to quantify the noise or vibration in a rotating machine whose rotational speed changes with time. In other words, it eliminates the influence of the change of running speed on the vibration signal analysis [4]. Order refers to a frequency that is a specific multiple of the reference rotational speed. For example, a vibration signal having a frequency equal to twice the rotational frequency of the motor corresponds to the second order, and a vibration signal having a frequency equal to 0.5 times the rotational frequency of the motor corresponds to 0.5 order. The calculation of order analysis is based on resampling interpolation technique. The method begins with an integer rotation of the estimated time $T_k(k = 1{:}K)$ corresponding to the axis (ie, the angle is equal to 2πk), defining the angular rotation vector : $\alpha_i = 2\pi\frac{iK}{N}$, the corresponding angular resolution is: $\Delta\alpha = \frac{K}{N}$. The resampling interpolation process is designed to convert a higher sampling rate isochronous measurement signal from the time domain to the angular domain, including two interpolation steps: the first step is to determine the exact moment of equiangular sampling based on the rotational time series:

$$t(i\Delta\alpha) = f(\{2\pi k, T_k\}, \alpha_i) \tag{1}$$

Where f(.) is an interpolation function.

In the second step, the original isochronous measurement signal y(jΔt) is interpolated at the time interval of the equal-angle sampling time, thereby calculating the vibration signal y(iΔα) in the angular domain required for the order analysis:

$$y(j\Delta\alpha) = f(\{y(j\Delta t), j\Delta t\}, t(i\Delta\alpha)) \tag{2}$$

2.2 Self-reference adaptive denoising

Because the vibration signal monitored on the bearing cover of the hoisting mechanism gearbox contains the gear signal, and it will seriously affect the vibration signal of the analysis bearing, it needs to be completed by self-adaptive noise cancellation (SANC). Separation of gear and bearing signals, SANC is an improvement over adaptive noise cancellation (ANC) technology, which was first introduced by Antoni (2004) [5].

The ANC compares the signals collected by the two sensors [6]. Taking the reduction gearbox as an example, the gear signal is collected as a reference signal, and the other acquisition includes the coupled signal of the bearing and the gear as the main signal, and subtracts the pass signal from the main signal. After the adaptive filter processing, the separation of the bearing and the gear signal is achieved by minimizing the evaluation index of the residual signal.

However, in the actual working conditions of this paper, it is difficult to obtain the "clean" gearbox gear signal as the reference signal, so this paper uses the ANC improved algorithm proposed by J. Antoni and RB Randall [5] - SANC algorithm, the schematic diagram is shown in Figure 2. The delayed signal of the original main signal is used as the reference signal, because when one of the original main signals is deterministic (discrete frequency) and the other is random, if the delay amount is greater than the correlation length of the random signal, then the adaptation filter does not recognize the correlation of the random signal, and will find the transfer function of the deterministic part and the delayed signal to achieve separation of the two signals. Because the gear meshing vibration in the gearbox is a deterministic periodic signal, and the bearing has a small slip, the bearing vibration signal is a random signal, so it can be separated by SANC.

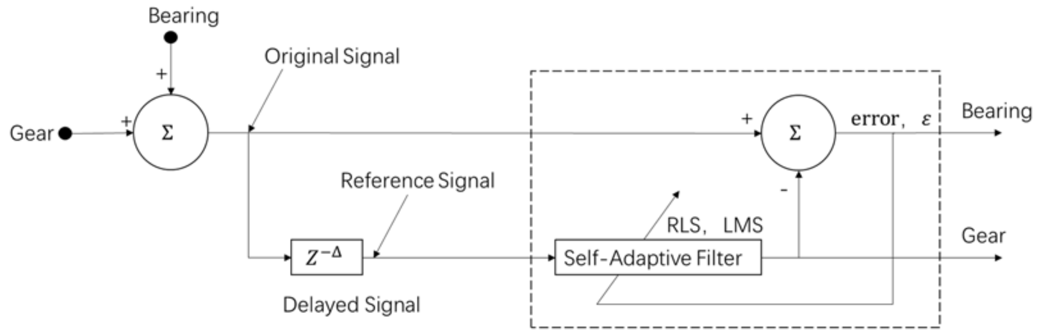

Figure 2: SANC algorithm schematic

The adaptive filter is a recursive filter, determined by a set of weight parameters, $[w_1, w_2 \dots w_L]$, where L is the length of the filter (should be much smaller than the signal length in order to adjust the weight during the recursive process, but it must also can distinguish between gear and bearing signal correlations). Taking the least mean squares (LMS) as an example, the weight vector recursion process is as follows:

$$\boldsymbol{W}_{k+1} = \boldsymbol{W}_k - \mu \nabla_k \tag{3}$$

Where the gradient vector is:

$$\nabla_k = \frac{\partial E[\varepsilon_k^2]}{\partial \boldsymbol{W}_k} \tag{4}$$

The LMS recursive process aims to minimize the mean square value of the error signal ε and bring it to (3). The weight vector calculation formula is approximated as:

$$\boldsymbol{W}_{k+1} = \boldsymbol{W}_k + \frac{2\mu_n \varepsilon_k \boldsymbol{X}_k}{(L+1)\hat{\sigma}_k^2} \tag{5}$$

Where μ_n is the normalized convergence factor, $0 < \mu_n < 1$, μ is the convergence factor, $\mu = \frac{\mu_n}{(L+1)\hat{\sigma}_k^2}$, ε_k is the kth recursion of the error signal, and $\boldsymbol{X}_k$ is k The order input signal, $\hat{\sigma}_k^2$, is the variance of the kth recursion of the input signal.

3 FEATURE EXTRACTION AND HEALTH ASSESSMENT

3.1 Feature extraction

The main methods of traditional bearing signal feature extraction are divided into time domain feature analysis, frequency domain feature analysis and time-frequency feature analysis. Time domain features include mean, variance, skewness, kurtosis, root mean square, peak, CrestFactor, ShapeFactor, ImpulseFactor, MarginFactor, and more. The frequency domain characteristics for bearing faults mainly include inner ring fault characteristic frequency, outer ring fault characteristic frequency, roller fault characteristic frequency, and cage fault characteristic frequency. The main methods of time-frequency analysis are short-time Fourier transform and wavelet transform.

3.2 Degradation trend analysis

Due to the large number of extracted feature values, the principal component analysis algorithm is needed to reduce the dimension, and the color is characterized by depth to light. As can be seen from the figure below, PCA1 is the main component.

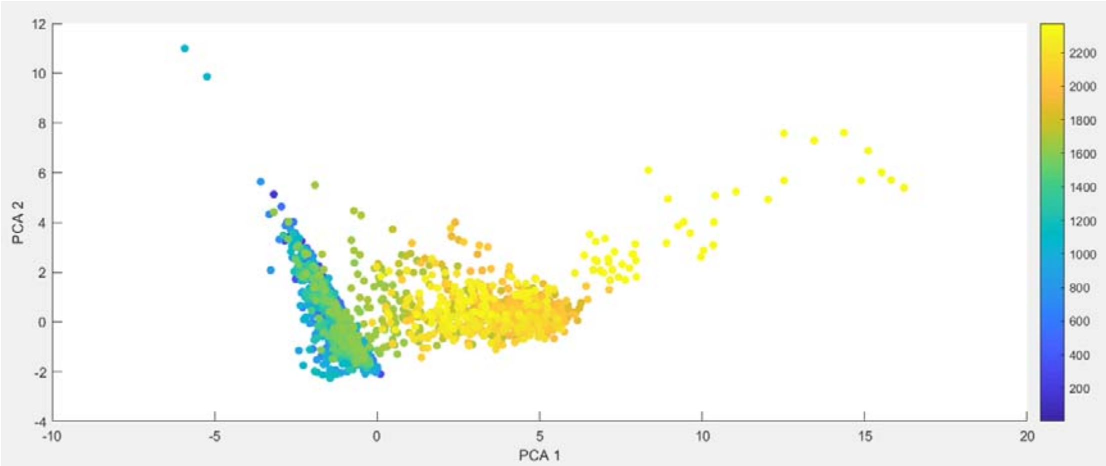

Figure 3: PCA

Taking PCA1 as the fusion characteristic index of bearing degradation degree, the trend of different bearing PCA1 over time is as follows:

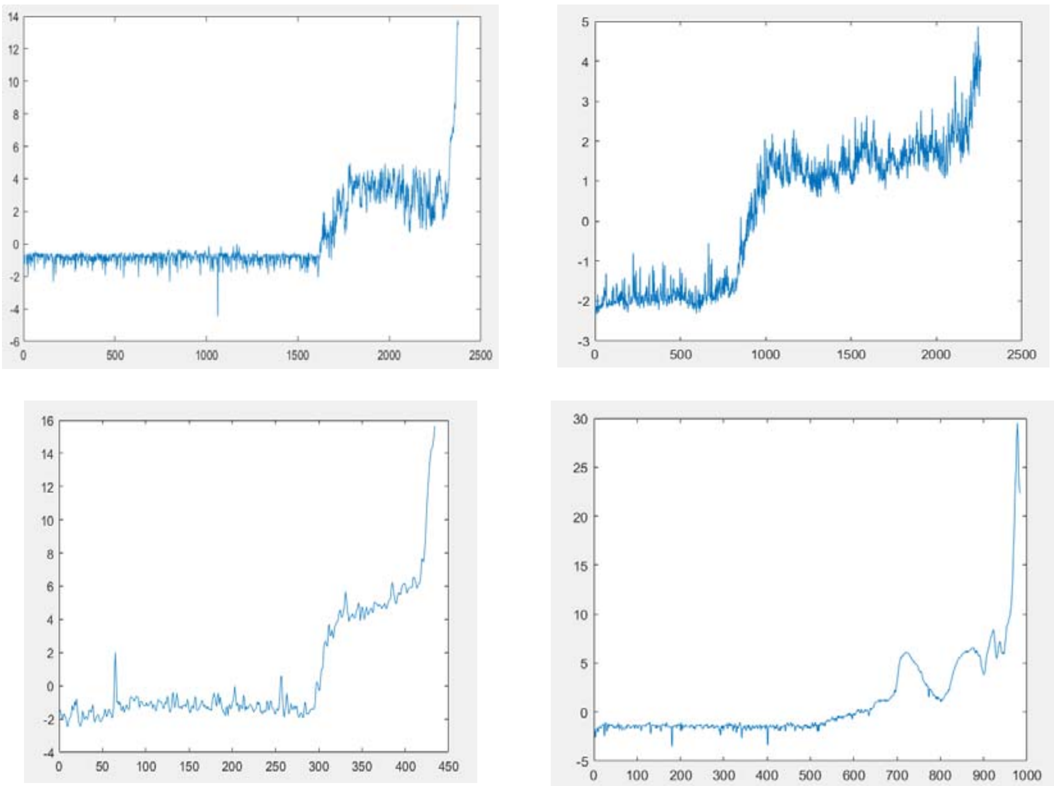

Figure 4: Bearing degradation trend curve

3.3 Abnormal detection

Common bearing fault detection methods are Spectral Kurtosis, envelope analysis.

3.3.1 Spectral Kurtosis

Spectral Kurtosis (SK) extends the concept of kurtosis into the spectrum. The original kurtosis indicator is a global indicator and cannot analyze transient information. By calculating the kurtosis value of the spectrum, non-stationary and anomalous signals can be identified and the frequency band containing the largest pulse can be determined. It was first applied to the pulse of the sonar signal. J. Antoni et al. (2006) [7] first conducted an in-depth and thorough study on the application of spectral kurtosis in bearing fault analysis. In the actual bearing diagnosis process, the collected vibration signal y(t) is a series of The sum of the impulse responses h(t) superimposed by the excitation pulse x(t).

$$y(t) = \sum_k x(\tau_k) h(t - \tau_k) \tag{5}$$

When the response function is an unsteady time-varying response, based on the Wold-Cramer non-stationary signal decomposition, h(t, s) is a time-varying filter (or time-varying response function), and x(t) is the original excitation signal. y(t) is a convolution of h(t, s) with x(t), expressing the response signal acquired after passing the response function.

$$y(t) = \int_{-\infty}^{t} h(t, t - \tau) x(\tau) d\tau \tag{6}$$

$$y(t) = \int_{-\infty}^{+\infty} e^{j2\pi ft} H(t, f) dX(f) \tag{7}$$

$H(t, f)$ is a time-frequency function and can be understood as the complex envelope of y(t) at the position of frequency f. In the actual vibration process, $H(t, f)$ is random, so it can be further improved to $H(t, f, \mathrm{v})$, where v is a random variable of the time-varying filter. At this time, the complex envelope is at the frequency f, and the 2n-order instantaneous distance at time t is its energy intensity, which is expressed as follows:

$$S_{2nY}(t, f) \triangleq E\{|H(t, f, v) dX(f)|^{2n} |v\}/df\} = |H(t, f)|^{2n} \cdot S_{2nX} \tag{8}$$

The average moment is obtained by averaging $S_{2nY}(t, f)$ after time domain integration:

$$S_{2nY}(f) = lim_{T\to\infty} \frac{1}{T} \int_{-T/2}^{T/2} S_{2nY}(t, f) dt \tag{9}$$

The fourth-order moment spectrum cumulant of the non-stationary process is defined as

$$C_{4Y}(f) = S_{4Y}(f) - 2S_{2Y}^2(f), f \neq 0 \tag{10}$$

The mathematical definition of spectral kurtosis is the normalized fourth-order moment cumulant:

$$K_Y(f) = \frac{C_{4Y}(f)}{S_{2Y}^2(f)} = \frac{S_{4Y}(f)}{S_{2Y}^2(f)} - 2, f \neq 0 \tag{11}$$

That is, the non-steady state random signal y(t) is measured, and the kurtosis of the signal envelope $(t, f, v) dX(f)$ mode in the time-frequency domain. In 2006 [8], J. Antoni and R.B. Randall proposed short-time Fourier Transform (STFT) for time-frequency analysis to solve spectral kurtosis analysis of bearing faults. It should be noted that the time window of the STFT must be shorter than the distance between two pulses, but must be greater than the width of one pulse. Antoni et al. recommend using Power Spectral Density (PSD) to determine the PSD as the above formula.(11), you can control the excessive smoothing or excessive peak caused by the window.

Since the bearing pulse fault signal has a higher peak at the dominant frequency and a very small amplitude at the frequency of the noise, the spectral kurtosis can be used as a filter. Let the signal y(t) be superposed by the pulse signal x(t) and the noise signal n(t): y(t)=x(t)+n(t), then the spectral kurtosis has the following relationship:

$$K_y(f) = \frac{K_x(f)}{[1+\rho(f)]^2} \tag{11}$$

Where $K_x(f)$ is the spectral kurtosis of x(t), and $\rho(f) = S_n(f)/S_x(f)$ is the inverse of the signal-to-noise ratio. Therefore, when the signal-to-noise ratio is high, that is, $\rho(f)$ is small, $K_x(f)$ is close to $K_y(f)$; conversely, at a frequency where the signal-to-noise ratio is small, $\rho(f)$ is extremely large, $K_y(f)$ It will approach zero and be filtered out. Therefore, the spectral kurtosis can be used as a filter to detect the frequency band of the bearing fault pulse signal.

Since the spectral kurtosis analysis of the original signal or the spectral kurtosis is dependent on the window selection of the short-time Fourier transform, in other words, the band-pass filtering of the output complex envelope $H(t,f)$ Bandwidth. Therefore, the spectral kurtosis is displayed as a function of the band window width as a parameter to obtain a two-dimensional image, a kurtogram, which can be used as a basis for bandwidth division of the bandpass filter in envelope analysis.

3.3.2 Envelope analysis

The spectrum of the original signal is often difficult to analyze, and the amount of information in the response is small. The envelope analysis was proposed in 1974 by Darlow [9] has been considered as the benchmark method for bearing fault diagnosis. Due to the extremely short duration of shock collision when the damage occurs on the working surface of the bearing, the frequency band is wide, and the excitation structure resonance makes the fault pulse increase, which is called high frequency resonance. It is often difficult to analyze the bearing fault from the spectrum. Therefore, it is necessary to carry out band-pass filtering on the high frequency band of the signal by using the envelope analysis technique, and then performing amplitude demodulation to form an envelope signal, which includes the fault diagnosis information.

Envelope analysis involves two methods, namely, square-based demodulation and Hilbert transform-based envelope analysis. The second method is more commonly used now, Hilbert-Envelope Analysis. Suppose that the original time domain signal X=Acos(ωt+φ) that needs Hilbert transform is obtained by Euler's formula:

$$X = Acos(\omega t + \varphi) = \frac{A}{2} \cdot e^{j(\omega t+\varphi)} + \frac{A}{2} \cdot e^{-j(\omega t+\varphi)} = X^+ + X^- \quad (12)$$

As can be seen from the above equation, X^+ is an analytical signal with only a positive frequency.

$$Y^+ = -jX^+, Y^- = jX^- \quad (13)$$

$$Y = Y^+ + Y^- = -jX^+ + jX^- \quad (14)$$

Y is the Hilbert transform of X, which is the result of summing the phase shifts of X^+ and X^- with 90^0. Thus, the analytical signal Z can be obtained:

$$Z = X + jY = X^+ + X^- + (X^+ - X^-) = 2X^+ = A \cdot e^{j(\omega t+\varphi)} \quad (15)$$

It can be seen from the above equation that Z has only the positive frequency of the original signal and the amplitude is twice that of X^+, which realizes the conversion of the bilateral spectrum of the original signal into a single-sided spectrum. The frequency domain transform according to the formula (13) Hilbert transform can be defined as:

$$H_{HT}(j\omega) = \frac{Y(j\omega)}{X(j\omega)} = j \cdot sign(\omega) \quad (16)$$

Where Y(jω) is the Fourier transform of the time domain signal Y; X(jω) is the Fourier transform of the time domain signal X. The impulse response function can be obtained by inverse Fourier transform as follows:

$$g_{HT}(t) = \frac{1}{\pi t} \quad (16)$$

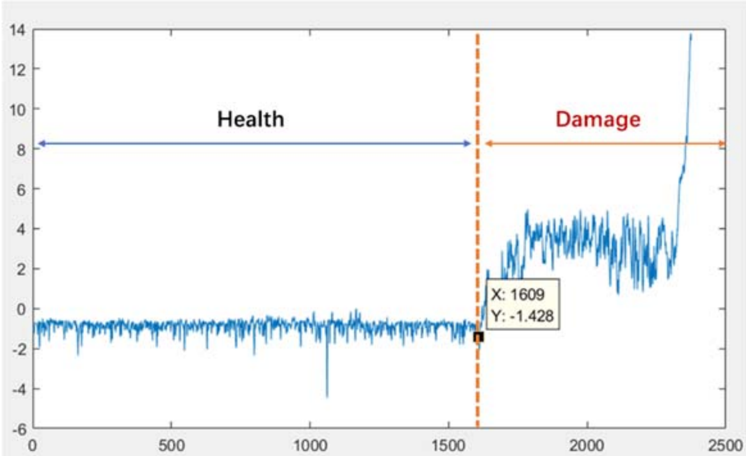

Figure 5: Bearing early fault point division

4 TRANSFER LEARNING FOR DIAGNOSIS

In this paper, based on AlexNet (Krizhevsky et al., 2012) [10] convolutional neural network, through the modification of the original AlexNet, a convolutional neural network suitable for classifying the bearing time-frequency image is completed. In recent years, feature-based migration learning methods are mostly combined with neural networks [11-14], and the migration of eigenvalues and models is also the core of this study. As the study of migration learning [15] shows that the main role of the layers in front of the deep neural network is the extraction of general features. The main role of the latter layers is to identify and classify the specific features, so it is necessary to make the layers behind the original network. Adjust, reinitialize the last three layers of AlexNet, and fine-tune the entire network. The input data set of neural network training is the time-frequency domain image obtained after wavelet transform (Figure 6). The health and damage image sets are classified according to the above degradation trend analysis and Hilbert-envelope analysis.

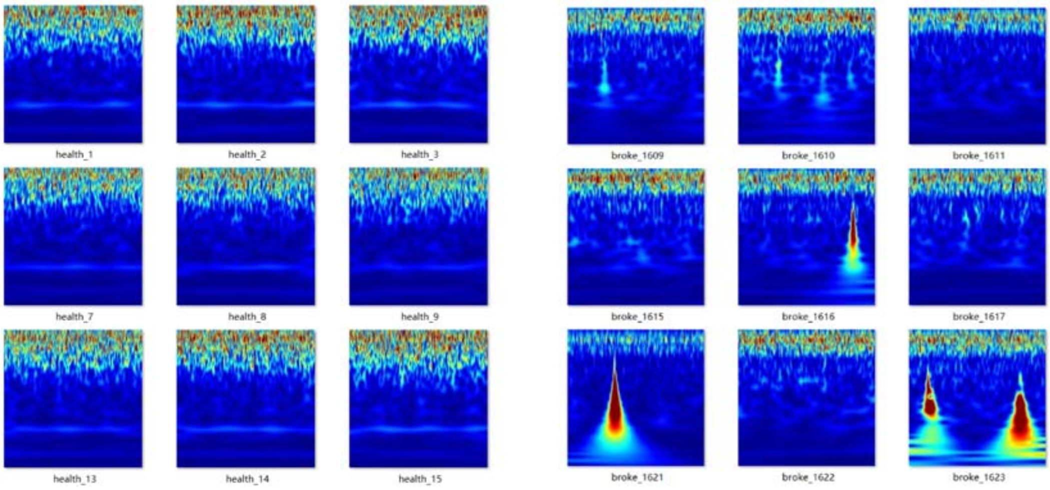

Figure 6: Time-frequency domain image obtained after wavelet transform

Firstly, we use the image sets of one bearing experiment to fine-tune the CNN. It can be clearly seen in Figure 7 that the accuracy of CNN fault detection by transfer the AlexNet is about 80% at first, and it is improved rapidly after fine-tuning. It proves that CNN is very effective in time-frequency domain image migration learning after wavelet transform of bearing vibration signal. And it converges quickly, which means When we extensively transfer this model to other online bearing diagnostics it can exert high timeliness in industrial applications.

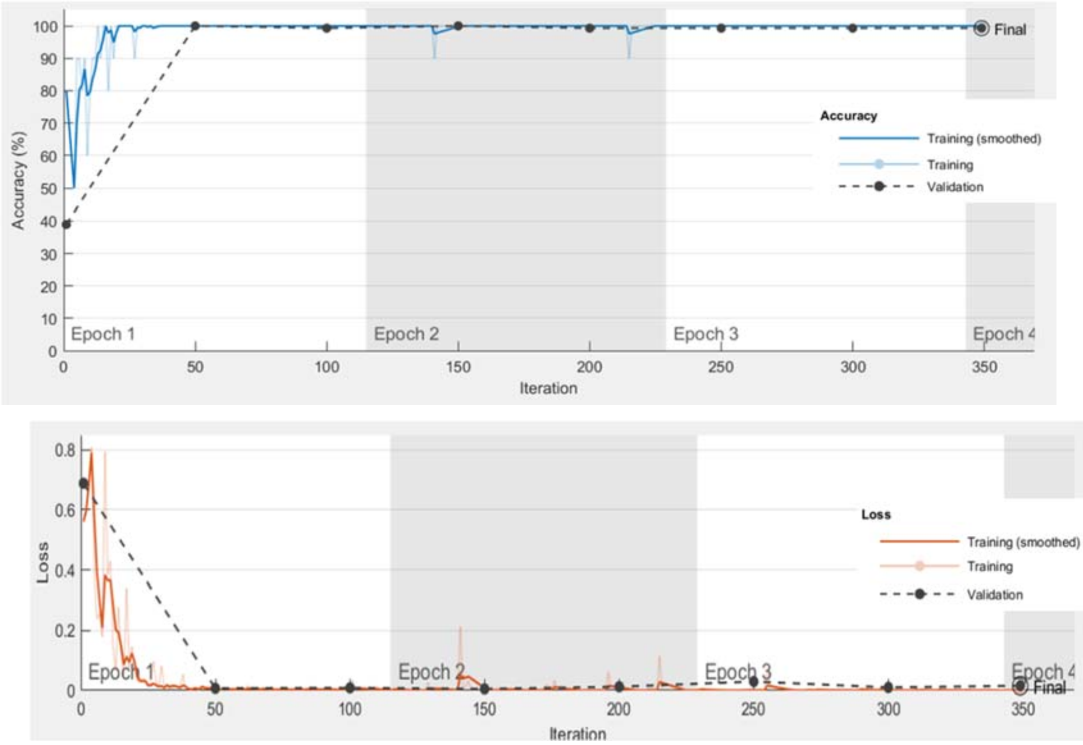

Figure 7: Transfer learning training results

5 CONCLUSION

At present, the bearing life prediction model proposed by GEBRAEEL (2005)[16] is widely used, which combined Bayesian and Exponential degradation model. The problem is that when the early failure occurs, the curve changes slowly and the prediction bias is large; There are some effective neural network prediction models, such as dynamic wavelet neural network (DWNN) [17]and LSTM. DWNN can be seen as a combination of recurrent neural network (RNN) and wavelet neural network (WNN). The wavelet function is used to replace the activation function in the neuron. It has the ability to recognize the abrupt signal, but the wavelet function needs to be adjusted according to different situations. Therefore, its generalization ability is poor; Although the LSTM can automatically adjust the impact of the longer time series on predicting the next moment, the training result cannot be effectively transferred to devices with different working conditions and life stage. There are few studies on the combination of fault pattern recognition and RUL prediction. This paper proves that CNN has good transfer ability in recognizing mechanical degradation. On this basis, piecewise prediction is a more universal scheme for online equipment health management. What needs to be improved is that the analysis of the degradation state of the bearing is too simple. If the pattern of the bearing failure and the degree of damage can be further distinguished, then the piecewise prediction can be expected to obtain a more accurate prediction result.

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