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Rolling Bearing Incipient Degradation Monitoring and Performance Assessment Based on Signal Component Tracking

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ABSTRACT To ensure a long-time stable operation of the rolling bearing, it is important to accurately assess their working performance, especially the incipient degradation based on the massive service process data. As a new and effective tool, deep learning model is applied widely in the field of fault diagnosis but limited to rare labeled data. In this paper, a bearing performance assessment method based on signal component tracking is proposed to realize the bearing degradation detection. More general features are obtained by local convolution operation to represent the local characteristics in the spectrum or time–frequency distribution of vibration signal, which follows the forward features mapping process of the convolutional neural network (CNN). Then, a novel quantification criterion based on the comparison of those local features is used to provide the selection strategy of optimal fault components. The proposed method takes into account the abnormal information in degradation monitoring and utilizes it to achieve bearing incipient fault diagnosis. The experimental results prove that the features extracted by the proposed method possess high recognition efficiency when being used in incipient failure detection and diagnosis.

INDEX TERMS Local feature, incipient fault diagnosis, performance assessment.

I. INTRODUCTION

As one of the most commonly used components in rotating machines, rolling bearings usually work with severe environment, such as heavy loading and high temperature, which can easily lead to defect. If there are no detection and warnings, the bearing defect can gradually develop into failure and finally cause unexpected loss for maintenance costs. The defect of bearings generates and aggravates gradually with time, and the detection of it demands higher requirements of features from vibration signal for both sensitivity and stability compared with features used in diagnosis [1]. The bearing condition monitoring is commonly separated from diagnosis, which means diagnosis of fault types are conducted independently based on the occurrence of abnormal state [2]. Considering the big data generated in service process of bearings, information of damage severity and fault types are buried in the time records, and more detailed information is expected to be obtained from process data monitoring and further for diagnosis recognition.

Estimating bearing condition at various stages of degradation is important for its maintenance decision. The proposition of degradation indexes is the main focus to reflect bearing degradation process [3]. Health indicators are commonly extracted from time, frequency and time-frequency domains of vibration signal and tracked to represent bearings performance [2], [4], [5]. Then identification of failure state is drawn based on the predefined threshold with prior knowledge [6] or intelligent models [7]. It is actually not ideal to describe degradation process using single metric now that it partially presents the suitability and is commonly biased. Meanwhile multiple indicators used to represent the

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degradation process may be redundant or conflicting with each other, especially when referring to the consistency of degradation trend. Moreover, the decision of condition monitoring is commonly binary. And when fault happens, manual inspections or further processes are conducted on vibration signal for diagnosis [2].

Aimed to avoid accident and provide timely maintenance, it is critical to select the most effective components from original signals for bearings incipient failure identification and performance assessment before final failure [4], especially those with characteristic frequency are worth noticing. Characteristic frequency of bearing incipient fault can be easily interrupted by noise or other masking sources in low-frequency band and meanwhile is found in a widely high-frequency band due to the modulation phenomenon [8]. Envelope analysis based on selection of optimal demodulation band has become an effective approach to recognize weak fault characteristic frequency, and thus different decomposition methods combined with component selection strategies were proposed, such as kurtogram and Protrugram [9], [10], minimum entropy de-convolution [11], singular value decomposition [12], ensemble empirical mode decomposition [13], [14], wavelet decomposition [15], intrinsic characteristic-scale decomposition [16] and local mean decomposition [17]. Moreover, multi-scale morphology filter [18] was also used lately for signal component extraction. Those optimal demodulation band selection methods mentioned were both established for faulty signal, and components selection strategies were conducted according to fault expertise. However, as we know, vibration signal components show diverse responses to the types and degrees of failure during bearing degradation process. And bearing incipient fault diagnosis is expected to be combined with its monitoring process, which is expected to provide more faulty information when the fault happens.

Considering the noisy and non-linear components in practical vibration signal as well as the powerful expression ability of deep learning, deep model instead of shallow model should be applied to investigate the rich information hidden in data. Convolution neural network (CNN) is one of the most commonly used deep learning models due to its shared weights and ability of local field representation [19]. Several variants of CNN are proposed and applied for fault diagnosis [20] and further employed to estimate the remaining useful life of critical components [21]. Since no prior information is available regarding the defect severity at various stages of bearing service process, learning-based models do not work for degradation assessment. Some researches have shown that neural networks with local random weights can obtain surprisingly good performance in classification. Extreme learning machine is combined with deep models to promote the ability of neural networks such as the learning speed and generalization performance [22]–[24]. In extreme learning machine, weights and bias in input and hidden units are chosen randomly according to specific probability distribution and remain unchanged during the training phase. Some researches [25]–[27] also pointed out that CNN with random filters can obtain good classification results, which seems to create spontaneous orientation selectivity. Research [28] employed CNN with random filters to extract features based on the STFT and proved that those features can be used for fault diagnosis.

In modern industry, signals for detection are usually obtained from complex operation processes, in which multiple unknown conditions exist and occur alternately, or several faults with the same component may lead to information coupling [29]. There is no enough prior knowledge to identify forthcoming fault in bearing degradation process. Another challenge is that it is difficult to adapt the model trained by one degradation process to another one, as there is similarity possibly but no repeatability between different processes. Moreover, features obtained from models trained with the fault data are actually the global or local optimal solution for classification, which is adaptive for fault diagnosis rather than monitoring. This is to say, there is no standard degradation process as reference to others, and general rather than optimized features are more suitable for monitoring.

Considering the problems mentioned above and the attractive advantages of CNN such as representation of local field and weight sharing, this paper proposed a bearing monitoring and fault diagnosis method using local features extracted by forward features mapping process of convolutional neural network. In the paper, local features are defined as the representation of local range corresponding to the specific area in spectrum and time-frequency distribution. It is obvious that various local features show different reflections to the specific degree of failure, and the aim of this paper is to track and detect the fault sensitive components of signal in bearing degradation process. Then comparison was conducted between local features to discover the most representative features and describe the current bearing states. Differences between internal structures in vibration signal are reflected from those local features to detect and diagnose the bearings incipient fault. The contributions of this paper can be summarized as follows.

1. To obtain more information of bearing degradation process, local features of vibration signal are extracted combined with spectrum or time-frequency distribution to represent and track the change of signal structure. It is found that high-dimensional local features actually reflect more detailed information of vibration signal.

2. Different from the original method, an incipient fault diagnosis method taking into account the information of degradation monitoring is introduced, which accomplishes early fault and condition partition according to fault sensitivity of local features.

3. According to the proposed method, CNN using kernels under a specific distribution without training can extract general rather optimal features and avoids the confliction of high-dimensional local features to some extent.

The paper is organized as follow. The basic theory of signal processing and convolution neural network is briefly introduced in Section 2. Section 3 depicts details about the proposed method. The method is verified on experimental vibration signal in Section 4, including the analysis of feature extraction process, application in condition monitoring and fault diagnosis, and then comparison is conducted in the same part. At last, section 5 gives the conclusion.

II. PRELIMINARY

A. STATISTICAL DISTRIBUTION OF VIBRATION SIGNAL

Frequency and time frequency distributions of vibration signal are obtained with fast Fourier transformation (FFT) and Short time Fourier transformation (STFT). For STFT, the signal is split into sections through window and processed using FFT in each section. The window function $\varphi(t)$ is positioned at τ on time axis of signal and then Fourier transform is utilized to calculate the spectrum of windowed signal.

$$F(\omega, \tau) = \int_{-\infty}^{+\infty} f(t)\varphi^{*}(t-\tau)e^{-j\omega t}dt \tag{1}$$

where ω and τ are respectively the modulation and translation parameter.

STFT is suitable for non-stationary signal due to its component of window, and a complex matrix S called time frequency distribution matrix is obtained after STFT and then transformed to a real matrix. In many researches, time frequency distribution matrix has been commonly regarded as time frequency image and processed with image processing techniques [30], [31]. More complete information is included in time-frequency image compared with spectrum analysis of vibration signal. Compared with common sequence and image, there is location and structure information in spectrum and time-frequency image whose coordinates bear clear meaning. Thus it becomes a key problem whether and where fault features will appear and how they vary from time for bearing degradation detection and performance assessment. In [2] and [32], spectral structure and sub-bands are tracked to monitor and determine the fault characteristic frequency based on the spectrum and time frequency image.

B. CONVOLUTIONAL NEURAL NETWORK (CNN)

Compared with other deep models like deep belief network and stacked auto-encoder, CNN owns the ability of local field representation, and we can obtain features characterizing local information of spectrum and time frequency distribution. Weight sharing reduces the number and complexity of parameters. As a result, each kernel actually determines its feature map. Considering those mentioned properties and following its forward features mapping process, we extracted multiple local features from spectrum or time frequency representation to monitor bearing running process in this paper.

Common convolutional neural network mainly includes feature mapping and training phase. The architecture consists of convolutional layer and pooling layer, with the style (alternating selective feature extraction and invariance-creating pooling) being the basis of convolutional networks [28]. In convolutional layer, several convolutional kernels are set up for feature mapping, and then a bias is added to the output of convolution operator. This process is formulated as follows:

$$y_j^l = \sum\nolimits_i x_i^{l-1} * k_{ij}^l + b_j^l \tag{2}$$

where x_i^{l-1} is the input of l convolutional layer, k_{ij}^l and b_j^l are respectively j kernel and bias corresponding to j kernel. y_j^l is the output of convolution operator denoted by $*$. It is then computed through the activation function. It is noted that the weights are shared in the same feature map and distinct among different maps.

$$x_j^l = \mathrm{sigm}(y_j^l) \tag{3}$$

where x_j^l is the output of l convolutional layer, sigm() denotes the sigmoid function, which is commonly used in neural network.

In the pooling layer, the number of feature maps stays unchanged but the resolution is reduced. The pooling operation is actually a down-sampling process, which generally includes maximum and average pooling. It guarantees some degree of invariance to input translations. The invariance to local translation can be a useful property when we care about whether some feature is present and where it is [27]. The feature maps in pooling layer is computed as follows:

$$x_j^l = \mathrm{down}(x_j^{l-1}) \tag{4}$$

where x_i^{l-1} and x_j^l are respectively the input and output of l pooling layer.

In the training stage, when an iteration of forward propagation has finished, back propagation algorithm is used according to squared error loss function. Common stochastic gradient descent based optimization method is utilized in network for parameters estimation to minimize the loss function [25]. The best mapping relations between data and target are established as a process of global optimization.

III. PROPOSED METHOD

Proposed method mainly consists of four steps. 1) Extraction and estimation of local characteristics in spectrum or time-frequency distribution. 2) The tracking of local features through whole degradation process signals and bearing performance assessment. 3) Selection of fault sensitive feature and bearing incipient fault recognition. 4) The features extracted can be applied for fault diagnosis.

A. BEARING DEGRADATION DESCRIPTION USING SPECTRUM OR TIME-FREQUENCY IMAGE

Statistical properties of bearing vibration signal can vary from time in whole degradation process, and short time Fourier transform is thus used to process vibration signals acquired at different timestamps. Meanwhile vibration signal can be stationary at specific time interval in bearing degradation process, and fast Fourier transform can be also used. When spectrum or time frequency image is applied to represent the bearing state at corresponding time, the degradation process can be described as a sequence of those signal representation with time, and the detection of it is actually the visual tracking application. Moreover, compared with common sequence and image, there is location and structure information in spectrum and time-frequency image whose coordinates bear clear meaning. Thus it becomes a key problem whether and where fault features will appear and how they vary from time for bearing degradation detection and performance assessment. In [2] and [32], spectral structure and sub-bands are tracked to monitor and determine the fault characteristic frequency based on the spectrum and time frequency image.

B. IMPROVED CONVOLUTION NEURAL NETWORK

Considering the ability of CNN representing the local field, we can obtain features of the local information of spectrum or time frequency distribution. Thus one-dimensional and two-dimensional improved convolution neural networks are established based on the spectrum analysis and time-frequency analysis. The key work in conventional CNN is the calculation of weights between layers, which are trained by standard back-propagation procedures and gradient descent algorithm according to the loss function commonly using mean squared-error [12]. In this paper, two-layer architecture of CNN is established, whose forward mapping process is reserved and training phase is omitted. Weights of the model are generated according to specific statistic distribution, and once the parameters are generated, they remain unchanged to deal with all samples.

As shown in Fig.4, take one dimensional CNN as an example. Suppose $\mathrm{x_i^{l-1}}$ is the input of l convolutional layer, and $\mathrm{y_j^l}$ is the output of convolution operator. K^l represents the kernel of L convolutional layer and $\mathrm{K}^l = [k_1, k_2 \ldots k_m]^T$, where $k_i = [k_{i1}, k_{i2} \ldots k_{in}]$ represents i kernel, m and n are respectively the number of kernels and the length of single kernel. There is no bias since training phase is omitted. For each kernel in convolutional layer, the element of which is selected randomly from $\{0, 1\}$, as follows:

$$y_i^l = \sum\nolimits_j x_j^{l-1} * k_{ij}^l \quad k_{ij}^l \epsilon \{0, 1\}; \tag{5}$$

For activation function, we adopt Leaky ReLu instead of sigmoid function in order to avoid saturation.

$$x_j^l = \begin{cases} 0.01 y_i^l & y_i^l < 0, \\ y_i^l & y_i^l \geq 0, \end{cases} \tag{6}$$

After convolutional layer, a maximum pooling without overlapping is used in pooling layer.

$$x_j^l = \mathrm{max\_pool}(x_j^l) \tag{7}$$

In the last layer of proposed network, the full connection layer is replaced and feature maps of different random kernels combined with average operation contribute to the extraction of local characteristic. Compared with original CNN, final feature corresponds to the local region of original spectrum and can be explained as energy of local frequency band.

$$y_i^l = (\sum\nolimits_i^m \sum\nolimits_j^n x_j^{l-1} * k_{ij}^l)/m \quad k_{ij}^l \epsilon \{0, 1\}; \tag{8}$$

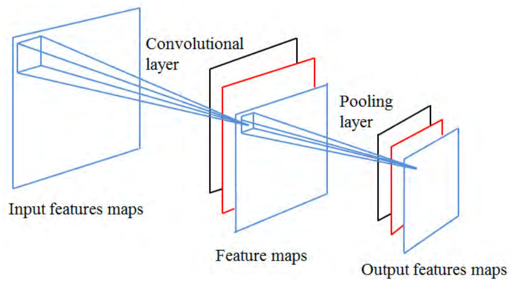

FIGURE 1. Convolutional layer and pooling layer in CNN.

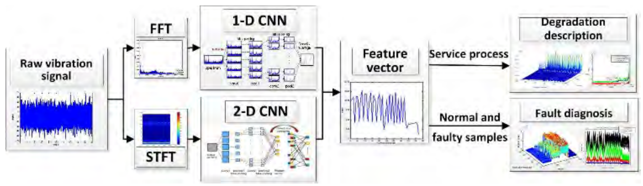

FIGURE 2. Proposed flow chart for bearing degradation monitoring and fault diagnosis.

Similarly, a two-dimensional CNN can be established based on the signal time-frequency analysis. No matter it is one or two dimensional CNN, the kernel in CNN is usually much smaller than the input, and each kernel is exert on every position of the input. Actually elements of kernel everywhere are zero except in this small, spatially contiguous receptive field [27]. Thus each convolution kernel can be regarded as a kind of band-pass filter acting on original input, and feature map as the response corresponds to each kernel.

C. SELECTION OF OPTIMAL DEMODULATION BAND

Feature vector is obtained using improved CNN to represent each record. It is obvious that each feature corresponds to the local field in spectrum and time-frequency distribution, and those local features obtained can be applied for bearing degradation detection and fault diagnosis. Considering the ability of local field representation and feature mapping rules in improved CNN, it is necessary to choose and track the fault sensitive features in bearing degradation process. And we further focus on the location relationship between the features extracted and original frequency band. For bearing vibration signal, those frequency sub-bands corresponding to fault sensitive features in degradation process contribute to the optimal demodulation band.

The range of original input covered by feature in the second pooling layer is related to the size of kernel, the size of pooling region and the length of stride. Take one dimensional CNN as an example and suppose the sizes of kernel and pooling region are 3 and 2, and the length of stride is 2. Fig.6 shows the mapping rule of one-dimension CNN, from which we can see that there is an overlap region between the ranges covered by adjacent features in the second pooling layer. In the last layer of proposed network, feature maps of another convolutional layer combined with average operation is given after the second pooling layer. As a result, the length

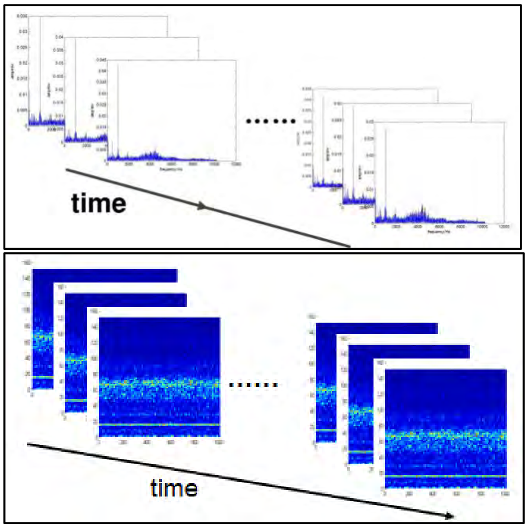

FIGURE 3. Description of bearing performance using spectrum (up) and time-frequency images (down).

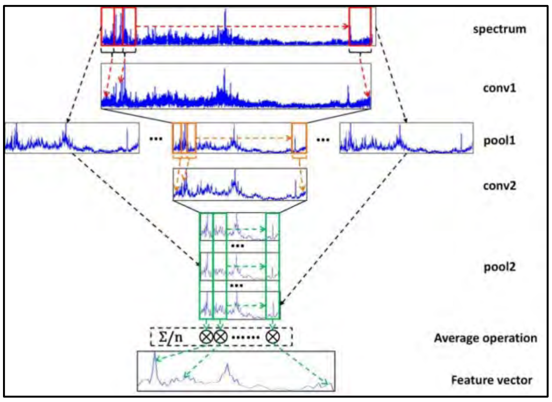

FIGURE 4. Structure of improved 1-D CNN.

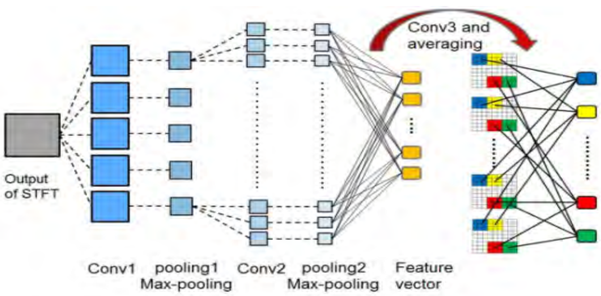

FIGURE 5. Structure of improved 2-dimentional CNN.

of the overlap region can be omitted compared with the range covered by a final feature and the corresponding range of original input is determined eventually according to the sequence of final feature.

IV. DATA EVALUATED AND RESULT ANALYSIS

Case 1 (Application in Bearing Degradation Monitoring): The data used for method verification is supported by

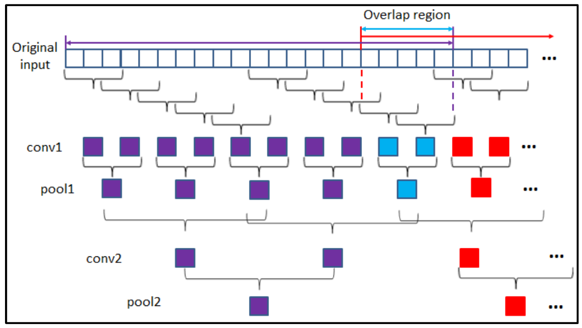

FIGURE 6. Mapping rule of improved 1-D.

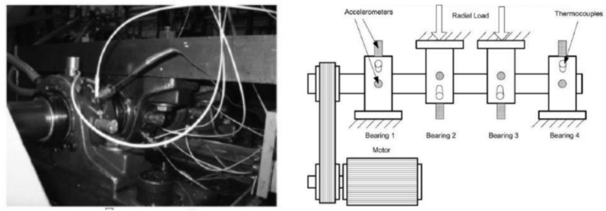

FIGURE 7. Structure of the experimental platform (left) and the position of the sensors (right).

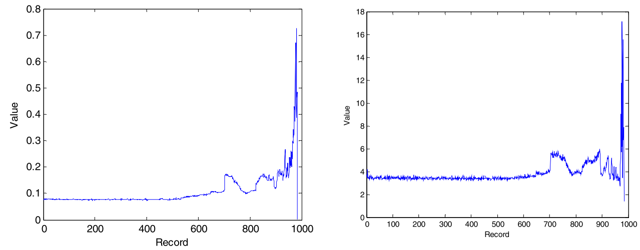

FIGURE 8. Representations of degradation using RMS (left) and kurtosis (right).

Intelligent Maintenance System, University of Cincinnati [27], and the bearing experimental system is shown as Fig.7. Four bearings were installed on the shaft. The rotation speed was kept constant at 2000 RPM by an AC motor coupled to the shaft via rub belts. A radial load of 6000 lbs is applied onto the shaft and bearing by a spring mechanism. All bearings are force lubricated.

Vibration data are collected with a recording interval of ten minutes. The sampling frequency is set at 20000 Hz and the length of each group of data is 20480 points. Since the RMS index is stable, it is generally used to represent the degradation process of bearings. Another commonly used index is kurtosis, which is more sensitive than RMS in detecting fault. Results using RMS and kurtosis index to represent bearing degradation process are shown in Fig.8, from which we can see that the record of early fault generating is difficult to be determined, especially when there is no prior knowledge for threshold setting.

The proposed method maps the local field in spectrum or time-frequency distribution into the specific feature, and represents the signal using feature vector. In the proposed

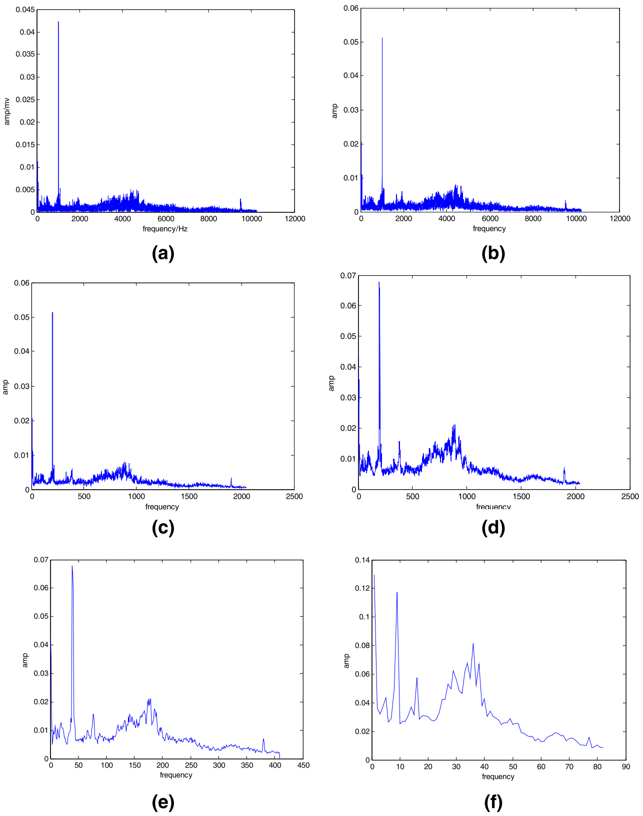

FIGURE 9. Visualization of feature mapping process in improved 1-D CNN. (a) Result of original spectrum. (b) Feature of first convolution layer. (c) Feature of first pooling layer. (d) Feature of second convolution layer. (e) Feature of second pooling layer. (f) Feature vector.

architecture, a two-layer one-dimensional convolutional neural network is established based on the spectrum. In convolutional layer, the number and length of the one-dimensional kernel are set as 5 and 8, and the stride we use is 1. Then a maximum pooling operation without overlapping is used in pooling layer and the length of pooling region is 5. The length of kernel in the last layer is set as 5. Those parameters of the model will leave an impact on dimension of the final feature vector, which determines the range in frequency spectrum that single feature corresponds to. The elements of each kernel are generated randomly, and remain unchanged to deal with all samples. Fig. 9 shows the visualization of mapping process for single signal where the convolutional network is actually known as a dimensionality reduction process, and local frequency information is preserved. Eventually, a vector consisting of 82 features is obtained for each record and arranged in time sequence to represent bearing degradation process.

Those features representing local frequency spectrum show different responses to various degrees of failure, and thus they are classified into different categories according to the fault sensitivity as shown in Fig.11. Bearing incipient degradation monitoring and performance assessment can be conducted based on the tracking for different types of features. A novel performance quantification criterion is then provided according to the variation of those local features,

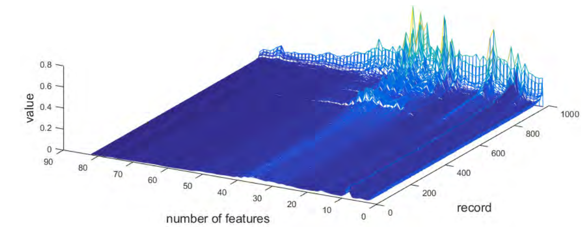

FIGURE 10. Description of bearing degradation process using feature vectors.

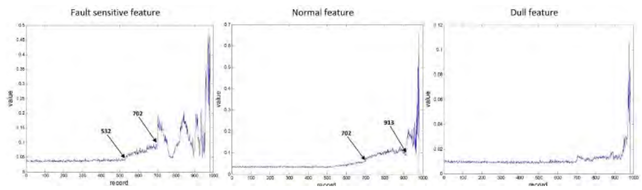

FIGURE 11. Local features extracted from spectrum.

and the analysis is conducted about which features contribute the most to the detection of current degradation. In this paper, high dimensional features are divided into three categories as shown in Fig.11, and they are fault sensitive features, normal features and dull features.

Compared with common time domain or other features, bearing incipient degradation time can be easily detected according to fault sensitive features, and so as the time when the fault aggravates. When fault sensitive features change at 532^{th} record, others still keep the original state. However, after 702^{th} record, it is difficult to further assess the bearing failure state in term of sensitive features because they change dramatically. And we can detect the failure time at 913^{th} record according to normal features, which is more stable than fault sensitive features in the whole degradation, and this type of feature is important for prediction of the remaining useful life. Once the bearing incipient degradation is detected at 532^{th} record, fuzzy clustering is applied to classify those local features from the first record to 532^{th} record, as shown in the left of Fig.12.

Considering the continuity of the same features, normal features are defined as those from first to 25th and dull features are defined as those from 40^{th} to 82^{th}. Those fault sensitive features are chosen to map into original frequency band, and they are features from 26^{th} to 39^{th}. Thus optimal demodulation band in this experiment is obtained according the sequence of fault sensitive features, which is from 3170Hz to 4756Hz. Fig.12 gives the correspondence between final feature and original frequency band. Then band-pass filtering and envelope analysis are conducted on fault sensitive band for incipient failure diagnosis.

A two-dimensional CNN can also be established based on the time frequency distribution. There are 5 kernels in each convolutional layer. Each kernel contains 5 rows and 5 columns, the elements of which are generated randomly from {0, 1}. The stride is 1. After convolutional layer,

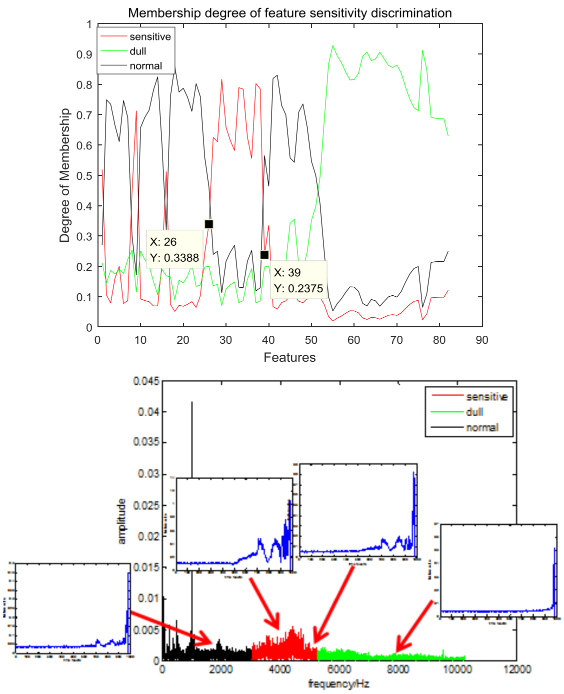

FIGURE 12. Clustering result of local features (up) and correspondence between original spectrum band and features (down).

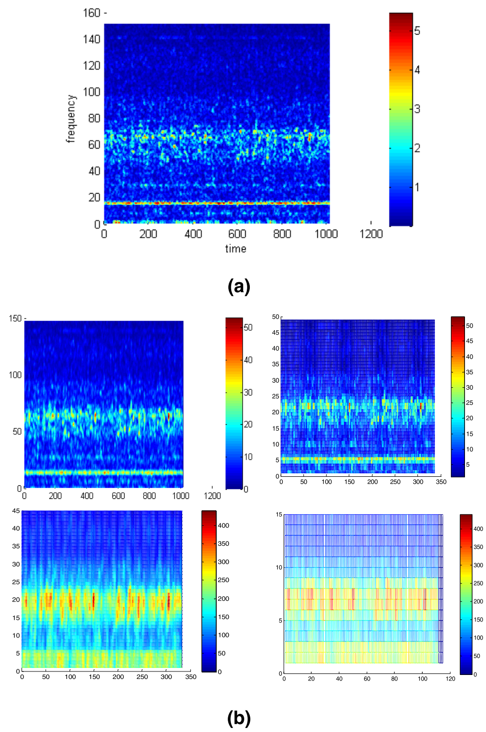

FIGURE 13. Visualization of mapping process in improved CNN. (a) Result of STFT. (b) Feature map of first convolution and pooling layer, second convolution and pooling layer.

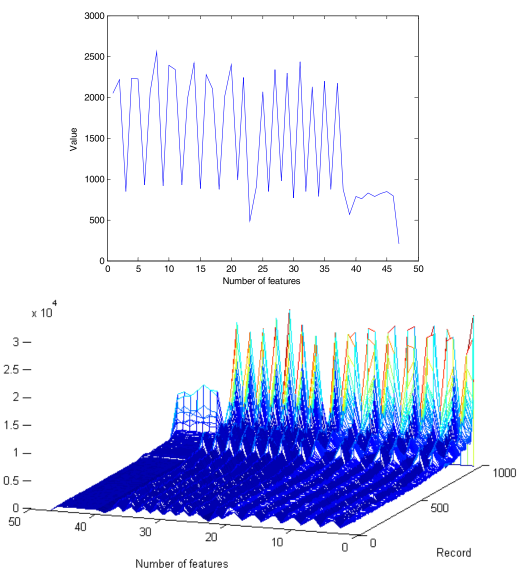

FIGURE 14. Feature vector extracted from one record (up) and description of whole life cycle using feature vectors (down).

a maximum pooling without overlapping is used in the pooling layer. Each pooling region contains 3 rows and 3 columns. The whole process finishes at one time without iterations, so the speed is significantly faster than common CNN. Fig.13 shows the visualization of non-linear mapping process in the architecture, from which the proposed convolutional network can be also known as a dimensionality reduction process, and useful information in time frequency image is preserved. At last, the vector consisting of 47 features is obtained for each record and arranged in time sequence to represent bearing degradation process.

High dimensional features obtained from two-dimensional CNN are also divided into three categories. They are sensitive features, ordinary features and dull features, which are represented by green, blue and red lines separately. According to Fig.16 (a), the values of sensitive features vary gradually after 532th record while the other two types still keep the original state, and 532th record is recognized as the time when early fault generates. After the generation of incipient fault, as shown in Fig.16 (b), ordinary features and dull features are still invariant until 702th record. At 702th record, there is a severe change in all features, which can be defined as the aggravation of fault. And after 702th record, it is difficult to assess the bearing state in term of sensitive features because they change dramatically. However, from Fig.16 (c), we conclude that ordinary features change slightly from 702th record until 912th record and dull features are stable relatively in this period. After 912th record, ordinary features started to rise rapidly and become unstable compared with dull features. This moment is recognized as the failure time when indication of downtime should be given. According to the analysis, some of those local features are sensitive while some are robust, which can provide assistance for each other to assess performance effectively.

Comparison: With the proposed method, we managed to identify early fault and assess the bearing condition by a new perspective based on the characteristic of CNN. Here we

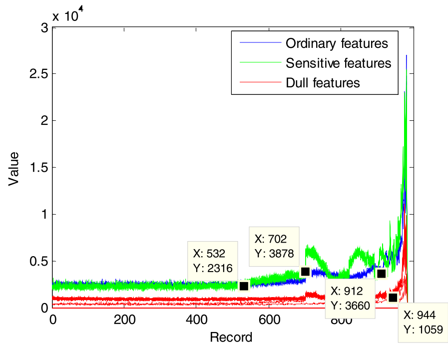

FIGURE 15. Classification of local features extracted from time frequency image.

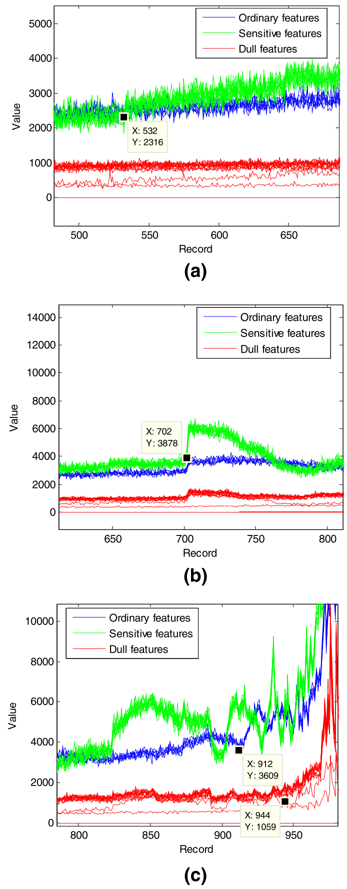

FIGURE 16. Representation of local features in the time of state change. (a) Occurrence of incipient fault. (b) Aggravation of fault. (c) Occurrence of failure.

give a similar approach combining wavelet and energy computation to represent bearing operation process and assess performance using high dimensional features. This method actually monitors the energy of each frequency band as the result of wavelet decomposition.

Original vibration signals are performed with 4-level wavelet packet decomposition, and the energy of each subcomponent is calculated and tracked. Fig.17 gives the representation of the whole life cycle of bearings. According to the result, features extracted by the proposed method show better

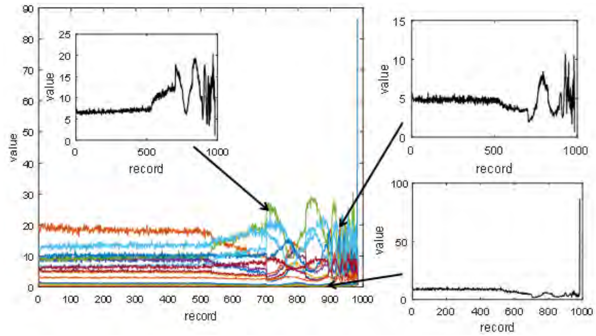

FIGURE 17. Description of bearing performance using the results of 4-level wavelet packet decomposition.

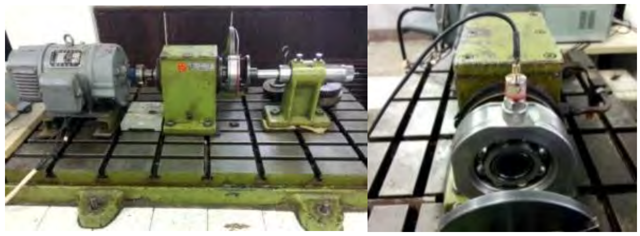

FIGURE 18. Bearing experiment platform for fault diagnosis.

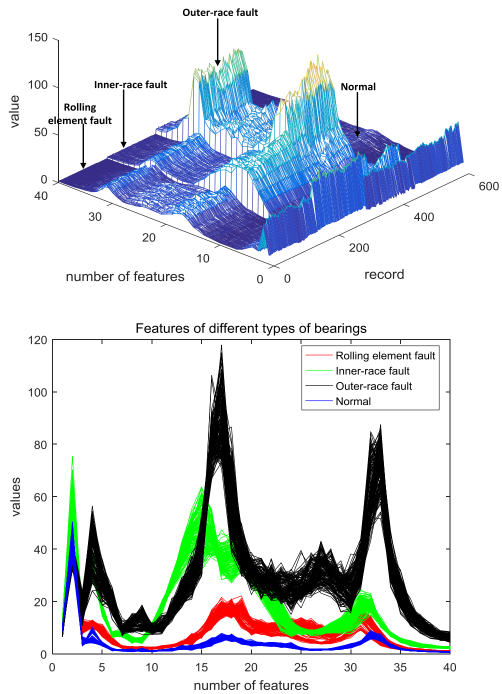

FIGURE 19. Feature vectors of different types of bearings.

consistency and those local features present more obvious difference in fault sensitivity, some of which are sensitive to the development of fault while others are more stable in the whole life cycle of bearings.

Case 2 (Application in Bearing Fault Diagnosis): In this section, the proposed method is also evaluated on rolling

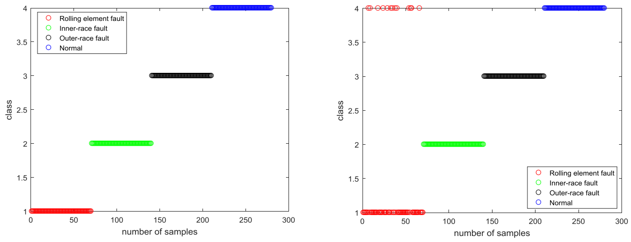

FIGURE 20. Fault classification results using proposed method (left) and common DBN (right) based on spectrum.

bearing dataset collected by accelerometers installed in bearing seat. The dataset consists of normal (NM) and faulty data whose single point faults exist in rolling element, inner race and outer race. The rotation speed was kept constant at 1200 RPM by the motor directly connected to bearing seat.

There are totally 600 groups of samples and 150 groups were collected for each type of bearings. The sampling frequency is 10000 Hz and the length of each record is 10000 points. One dimensional improved CNN is used and the result of FFT for all samples is as input into the model. The parameters of improved CNN are generated randomly and remain unchanged to deal with all samples. Feature vectors representing original data were then obtained and then used for fault classification. As shown in Fig.19, a 40-dimension feature vector is obtained for each record. According to the results in Fig.19, it is clear that features extracted by proposed model show obvious divergence among different types of bearing and similarity in same type. Those local features extracted by improved CNN are used for bearing performance monitoring online, and fault diagnosis can also be conducted based on the same features.

Considering the high dimensions of local features extracted, we establish another two-layer DBN after improved CNN, and single soft-max layer is used for diagnosis. Then 80 groups of data from each type of bearing are selected randomly as training sets and others for testing. Fig.20 shows that single soft-max layer succeeds in fault diagnosis and obtains high accuracy.

Comparison: The proposed model consists of a two-layer untrained CNN and a two-layer common DBN based on original spectrum of vibration signal, the total number of layers is four. With comparison, we also set a four-layer DBN based on original spectrum for diagnosis and show the classification result in Fig.20. The structures of the models used are shown in Table.1. When the same reconstruction and training error thresholds are set, the average time for training and testing in the proposed model is only 73 seconds while it is 1905seconds for the four-layer DBN, and most of the time in four-layer DBN is used for the pre-training of the first and second restricted Boltzmann machines.

It is concluded that the proposed architecture obtains local features without labeled data, and when combined with shallow DBN, it provides good performance of classification in accuracy and effectiveness. And it can be thought that any time when you need a matrix which is too complicated to study, you can try replacing it with a random matrix and calculate averages [33]. Results of data verification indicate that kernels generated from specific distribution combined average operations contribute the extraction of inherent characteristics in original signal, and the result shows effectiveness of the features when used for degradation monitoring and fault diagnosis.

TABLE 1. Structures of the model.

Model	Number of nodes						
	Input	Layer1	Layer2	Laye-r3	Laye-r4	Out-put	Acc (%)
Proposed method	Unsupervised CNN			Supervised DBN			100
	Spect-rum (5000)	Con1(1*8*5)+Pool1(1*3)	Con2(1*8*5)+Pool2(1*3)+con3(1*6*1)	60	20	5	
DBN	Spect-rum (5000)	1000	300	80	20	5	95.4

V. CONCLUSION

In this paper, the proposed method combining FFT, STFT with promoted convolutional neural network is able to capture the representation of local region in spectrum and time frequency distribution through multiple nonlinear mapping. Different from common monitoring method, we described bearing degradation process using high dimensional local features instead of single indicator. And detailed information of internal structures in vibration signal is reflected from those local features. A novel performance quantification criterion is provided to detect incipient degradation and other degrees of failure. The proposed method recognizes the incipient degradation effectively without prior expertise according to data analysis. It is analyzed that random kernels combined average operations contribute to the extraction of inherent characteristics in original signal and the attempts show good performance. The paper focuses on the correspondence between the features extracted and local field of original input, combined with prior knowledge of fault sensitive features in degradation process to diagnose the incipient fault directly when novelty are detected. Meanwhile the experimental result shows that those features are effective for fault classification.

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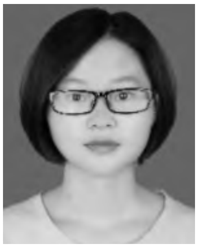

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