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Data Preprocessing Techniques in Convolutional Neural Network based on Fault Diagnosis towards Rotating Machinery

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ABSTRACT Rotating machinery plays a critical role in many significant fields. However, the unpredictable machinery faults may lead to the severe damage and losses. Hence, it is of great value to explore the precise approaches for fault diagnosis. With the development of the intelligent fault diagnosis methods based on deep learning, convolutional neural network (CNN) has aroused the attention of researchers in machinery fault diagnosis. In the light of the reduction of difficulty in feature learning and the improvement of final diagnosis accuracy, data preprocessing is necessary and crucial in CNN-based fault diagnosis methods. This review focuses on CNN-based fault diagnosis approaches in rotating machinery. Firstly, data preprocessing methods are overviewed. Then, we emphatically analyze and discuss several main techniques applied in CNN-based intelligent diagnosis, principally including the fast Fourier transform, wavelet transform, data augmentation, S-transform, and cyclic spectral analysis. Finally, the potential challenges and research objects are prospected on data preprocessing in intelligent fault diagnosis of rotary machinery.

INDEX TERMS Data preprocessing, convolutional neural network, intelligent fault diagnosis, rotating machinery.

I. INTRODUCTION

Rotating machinery is widely used in many fields, including aerospace, navigation, wind turbines and so on. On account of the intensity of operation and varying working conditions, the frequent machinery faults may result in the unexpected severe losses in safety and economy [1,2]. As a typical interdisciplinary cooperation, fault diagnostic techniques can be categorized into the following three categories, model-based methods, knowledge-based methods, and signal-based methods [3].

Numerous studies have been performed via common fault diagnosis methods, which express great limitations in complicated feature extractions [4, 5]. Combined with artificial intelligence and fault diagnosis, intelligent diagnostic methods can be considered to be a part of knowledge-based approaches and be capable of automatic learning [6,7,8]. Intelligent diagnostic approaches are usually classified into shallow-layer based model and deep-layer based model. With the development of deep learning, deep neural network (DNN) based methods have motivated the research of fault diagnosis approaches [9,10,11]. Among them, convolutional neural network (CNN), deep belief network (DBN), and deep autoencoders (AE) have been viewed as prevailing and striking in fault diagnosis of rotating machinery [12,13,14,15,16]. CNN stands out as a result of its special strengths in automatic learning ability, which can implicitly learn from training data and achieve feature extraction via the contribution of convolution kernels [17]. In the light of bearing fault diagnosis, different methods based on CNN were developed, with new training strategies and aiming at imbalanced distribution problems of machinery data [18,19]. Pan et al. employed the LiftingNet framework to analyze the fault type and severity, taking the changing rotating speed and working conditions into account [20].

Through the above analysis, some achievements have been made on DNN based intelligent fault diagnosis, which have been demonstrated that classification performance and generalization capability can be enhanced via some of the discussed methods [21,22,23]. The approaches mentioned above have certain requirements for data, such as two dimensional images and matrices, grayscale or the spectrogram of a special size. Namely, not all data can be directly identified as desired inputs. Therefore, it is imperative to explore the suitable preprocessing methods of raw collected data before the classification steps. If it is difficult to achieve the acquisition of original fault data, the amount of data collected may be limited and insufficient for input of DNN. Under this circumstance, it is necessary to expand the data capacity to meet the requirements of the following training operation [24,25,26]. Guo et al. employed fast Fourier transform (FFT) to accomplish the conversion of the vibration signal for fault diagnosis of wheel bearing [27]. In spired by the Order Tracking and FFT, Hu et al. developed a new data augmentation algorithm which combined data simulation by resampling and FFT, and integrated it with CNN for bearing fault diagnosis [28]. More intuitive classification results can be obtained by 2D CNN based methods, but raw data needs to be transformed into images as the requested input [29,30,31]. In view of the limitations of feature representation of raw vibration signal, some signal processing techniques have been exploited to intelligent fault diagnosis, such as short time Fourier transform (STFT), and the wavelet transform (WT) [32,33]. Hoang et al. developed a new CNN method on the basis of LiftingNet to validate the classification performance under noise interference, with a spectral image transformation via FFT [34]. Zhu et al. employed STFT to transform vibration signals into 2D time-frequency graphs, which were taken as the input of CNN on the basis of capsule network [35].

In intelligent fault diagnosis based on DNN, the appropriate data preprocessing will be conducive to subsequent training of network and provide some assistance to enhance the accuracy of fault diagnosis. This review concentrates on the applications of CNN-based approaches for intelligent fault diagnosis of rotary machinery. Firstly, the basic architecture and principle of CNN is outlined. Then, data preprocessing in CNN-based methods are talked about. And the employment of data preprocessing techniques included in the above methods are emphatically analyzed and discussed, primarily involving WT, S-transform (ST), data augmentation, cyclic spectral analysis and other techniques. Finally, the challenges and prospects of data preprocessing are provided in intelligent fault diagnosis towards rotating machinery.

II. DATA PREPROCESSING APPROACHES IN CNN-BASED FAULT DIAGNOSIS

In regard to conventional fault diagnosis, data preprocessing is usually used to accomplish feature extraction by means of the elimination of noise interference, involving many steps [36 , 37 , 38]. With an integration of alternative signal acquisition, feature extraction and fault classification in traditional fault diagnosis, intelligent fault diagnosis presents the potential in developing novel fault classification techniques [39,40,41]. However, in view of training process of the designed model, sufficient data input should be requested; especially, image input can be satisfied for such methods as 2D CNN based methods [42,43]. Therefore, in order to achieve the increase of data and the transformation of the demanded 2D image, it is still essential to perform data preprocessing before the following network learning.

A. CNN BASED INTELLIGENT FAULT DIAGNOSIS METHODS

On account of the characteristics of diversity, nonlinearity and high dimension in machinery data, deep learning based diagnostic technology demonstrates the superiority over traditional methods greatly dependent on human experience [44 , 45 , 46]. In terms of the learning of effective and distinguished features, CNN overcomes the drawbacks of multiple parameters and local invariance in fully connected feedforward neural network, and has been considered to be a promising tool to reduce overfitting for fault diagnosis by means of supervised learning [47,48].

CNN involves data input layer, convolution layer, ReLU activation layer, pooling layer and fully connected layer. The feature extraction and classification can be achieved by the structural layers. It is worth pointing that three traits of CNN makes it superior to other DNN methods, including local connection weights sharing and down-sampling. It is the root cause to implement the reduction of parameters and overfitting. Convolution layer and pooling layer are the special compared with other networks. With respect to the local connection in the convolutional layer, each neuron is connected to the neuron in a local window in the next layer, and every kernel is considered as a local window.

The convolution layer is essential in CNN. Firstly, the data is input into the network. Then the convolution operation is conducted on the input data through the convolution kernel. The weights and bias are updated during the process. Ultimately, the output is acquired via the nonlinear function.

In signal processing and image processing, the frequently-used CNN includes 1D and 2D structure. Thereinto, 1D convolution can be primarily employed to signature process to calculate the delay accumulation of signals. It can be achieved that the different characteristics of signal series can be extracted by devising various filters. Moreover, as an extension of 1D convolution, 2D convolution has been widely used to image process, which is viewed as an effective method for feature extraction [49,50].

In terms of the special structure of convolution layer and characteristics of CNN, CNN displays the potential capability of automatic feature learning. CNN-based intelligent diagnostic methods present the superiority in decrease of the dependence of expert diagnostic experience and preprocessing methods. However, necessary data preprocessing can enhance the diagnostic performance of the methods.

B. DATA PREPROCESSING IN INTELLIGENT FAULT DIAGNOSIS

Numerous researches on data preprocessing have been successfully performed in traditional fault diagnosis, including fractional Fourier transform, WT, FFT and Hilbert vibration decomposition [51,52,53]. Rai et al. analyzed the merits and demerits of applications of signal processing in fault diagnosis towards rolling bearings from three different stages, which provided beneficial references for the expected feature representation [54]. Kumar et al. researched a new information fusion method for gearbox fault diagnosis, employing discrete wavelet features in the process [55]. Some data preprocessing methods are also used in intelligent fault diagnosis of machinery [56,57,58]. On the basis of Wasserstein generative adversarial network with gradient penalty, a new data augmentation method was developed for fault diagnosis [59]. A new deep feature learning method was constructed for fault diagnosis of rotating machinery, and feature-level fusion instead of data-level fusion was combined in the research [60].

III. APPLICATIONS OF DATA PREPROCESSING APPROACHES IN CNN-BASED FAULT DIAGNOSIS

With the increase of mechanical failure data and coupling complexity, intelligent fault diagnosis on the basis of DNN has drawn the interest of researchers owing to the potent capability of extraction and admirable learning ability [61,62,63]. From the perspective of the requirements for input data, not all DNN-based methods could directly process raw vibration data for the final defect classification and prediction. Such methods are not viewed as end-to-end approaches, therefore, data preprocessing technique plays a crucial role in the intelligent fault diagnosis [64,65,66]. In the light of the advantages of CNN in intelligent fault diagnosis, this review will play an emphasis on the analysis and discussion of CNN based diagnostic methods [67,68].

Before the raw experimental data can be taken as input of the CNN model, it is necessary to relieve learning stress of model by means of preliminary signal analysis [69]. Many signal analysis strategies have been employed, including 1D data-based and 2D data-based approaches. With respect to the raw time domain data, the conversion of matrixes can be taken into account. The FFT can be used to analyze frequency domain data. In regard to 2D time and frequency domain analysis, some effective methods have been exploited to accomplish the complex transformation in the field of signal processing, STFT, ST, and WT included.

A. WAVELET TRANSFORM

One of the drawbacks as for the STFT analysis, the acquired frequency resolution is not variable. In consideration of high frequency band, ST is viewed as disadvantageous. Owing to the feature consistency of signal conversion, WT is considered to be a desirable method for time-frequency imaging analysis, which can accomplish the representations from different standpoints in regard to high and low frequency features in distinct scales respectively [70,71].

In general, the WT can be classified as the following three types, discrete wavelet transform (DWT), continuous wavelet transform (CWT), and wavelet packet transform (WPT) [72]. With the progress and applications of WT in fault diagnosis of rotary machinery, the second generation wavelet transform is included as well [73]. In regard to all these methods, it is of great significance to choose the suitable wavelet basis, which will be conducive to potent fault diagnosis.

With respect to the fundamental theory of WT, brief mathematical description can refer to the relative researches [74,75]. The mother wavelet can be expressed in the following,

$$\psi_{u,s}(t)=\frac{1}{\sqrt{s}}\psi(\frac{t-u}{s}) \tag{1}$$

Among them, $\{\psi_{u,s}\}$ denotes the wavelet dictionary generated by a single wavelet; there are two variables, s and u respectively; the parameter s denotes the scale and $s>0$, which is used to control the scaling of the wavelet function; u represents the translation and $u \in R$, which is employed to regulate the translation of the wavelet function.

The corresponding WT can be represented as follows,

$$W_f(u,s)=\left\langle f,\psi_{u,s}\right\rangle=\frac{1}{\sqrt{s}}\int x(t)\psi(\frac{t-u}{s})dt \tag{2}$$

Different wavelet analysis methods have been applied to the intelligent fault diagnosis of rotating machinery. Inspired by the learning difficulty of complicated CNN model, Liang et al. employed WT to acquire the preliminary feature extraction of raw vibration data, satisfying the requirements for 2D images of CNN input [76,77]. In comparison to raw data, the transformed images laid the foundation for the following automatic feature learning and enhancement of expected classification performance.

A hierarchical diagnosis network was constructed for fault diagnosis of bearing, and the wavelet packet transform was employed to feature extraction [78]. In order to diagnose the fault of gas turbine, a new method was investigated by Guo et al. combined continuous WT and CNN [79].

However, in the light of the shortcomings in large number of redundant coefficients in continuous wavelet transform analysis, DWT has the special superiority of powerful information processing ability in machinery fault diagnosis [80,81]. By means of DWT, raw data were transformed into time-frequency matrixes, which were taken as input of the following CNN model for fault diagnosis of planetary gearbox [82]. The process of DWT was displayed in Figure 1. The employment of time-frequency matrixes made the obtained feature representation more comprehensive, in

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addition, the learning of nonlinear relationships was achieved as well.

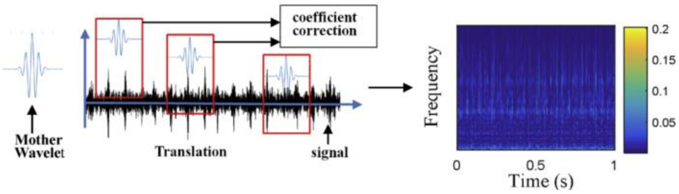

FIGURE 1. Schematic diagram of discrete wavelet transform execution process.

B. S-TRANSFORM

FT can only be used to process convergent signals, and STFT possesses the immutable window function. With regard to WT, although its window function is variable and can be used for multi-resolution analysis, it is difficult to select the basis function. Therefore, combining with the advantages of the above methods, S-transform eliminates the screening of window function and makes up for the defect of fixed window width. The phase spectrum of each frequency component in the time-frequency representation is directly related to the original signal. Moreover, the resolution can be adjusted adaptively and its inverse transformation is lossless and reversible.

The ST was a time-frequency analysis method proposed by Stockwell [83]. The ST of a function $x(t)$ is defined as:

$$S(\tau, f)=\int_{-\infty}^{+\infty} x(t)\omega(t-\tau)e^{-j2\pi ft}dt \tag{3}$$

Among them, τ represents the time of spectral localization, f denotes the Fourier frequency, and $\omega(t)$ represents the window function.

$$\omega(t)=\frac{|f|}{\sqrt{2\pi}}e^{\frac{-t^2f^2}{2}} \tag{4}$$

Gaussian function is an exponential function which describes the relationship between time and frequency, the width of the window and the frequency present inverse proportional. When window function $\omega(t)$ is replaced by the Gaussian function (Eq. 2), the ST can be accordingly expressed by

$$S(\tau, f)=\int_{-\infty}^{+\infty} x(t)\frac{|f|}{\sqrt{2\pi}}e^{\frac{-(t-\tau)^2f^2}{2}}e^{-j2\pi f}dt \tag{5}$$

To conduct gearbox fault diagnosis, a seven-layer LeNet-5 was utilized by Zeng et al [84]. Owing to the requirement of two-dimensional input in CNN, raw vibration signals under ten varying working conditions were transformed to time-frequency spectrogram by the use of S-transform. It can be found that different time-frequency images were obtained with regard to changing fault patterns, and two energy-concentrated frequency bands were observed approximately 1500 Hz and 2500 Hz (Figure 2). The CNN discussed above achieved and average classification rate of 99.37% and computation time of 169.91 seconds as well, which displayed the superiority to stacked autoencoder (SAE) and deep belief neural network (DBN) for comparisons.

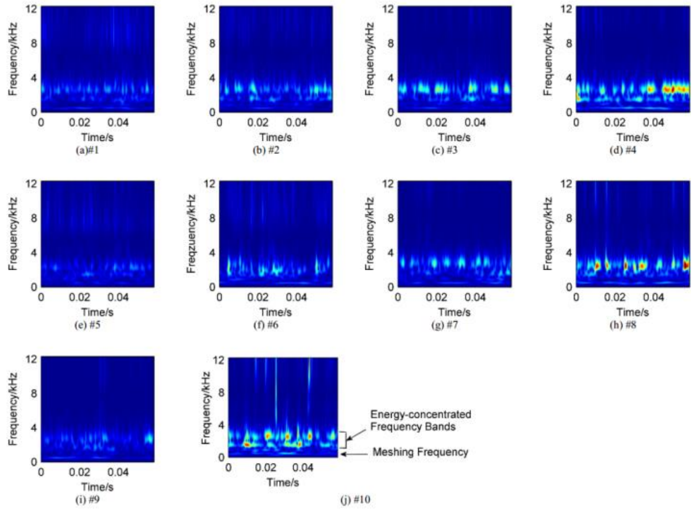

FIGURE 2. Time-frequency distribution of different vibration signals.

On account of the type and degree of failure in the meantime, a novel hierarchical CNN based on LeNet-5 was constructed for bearing fault diagnosis, with a structure of multiple shared layers and two respective classifiers. Before network training, S-transform was employed to convert fault data into time-frequency distribution images [85]. In terms of experimental design, for comparison, three different cases were adopted with reference to three relative researches under the various operation conditions and workloads [86,87,88].

C. CYCLIC SPECTRAL COHERENCE

As one of attractive signal processing methods, cyclic spectral analysis presents the special strengths in analyzing cyclostationary signals in comparison to other methods, such as spectral kurtosis, envelope analysis, and short-time FT [89,90,91,92,93]. Cyclic spectral correlation can be the considered as double FT of the signal, which depicts the relationship of the spectral frequency f and the cyclic frequency. In view of the deficiencies of conventional cyclic spectral analysis in data processing under noisy environment, a more effective tool called cyclic spectral coherence (CSCoh) includes extra frequency dimension, with the sensitive advantage of processing cyclostationary signals [94,95,96].

CSCoh was introduced to perform initial feature learning by preprocessing raw vibration signals, moreover, the hidden periodic behaviors were elucidated with regard to different failure patterns. Through integrating the classification superiority of CNN with the feature extraction capability of CSCoh, a new intelligent approach was developed for fault diagnosis of motor bearings [97]. As can be seen from Figure

3, different harmonics represents the special features of the specific defects. Furthermore, generalization ability was enhanced by exploiting group normalization. The advantageous average accuracy of 98.93% was obtained in comparison to other similar approaches.

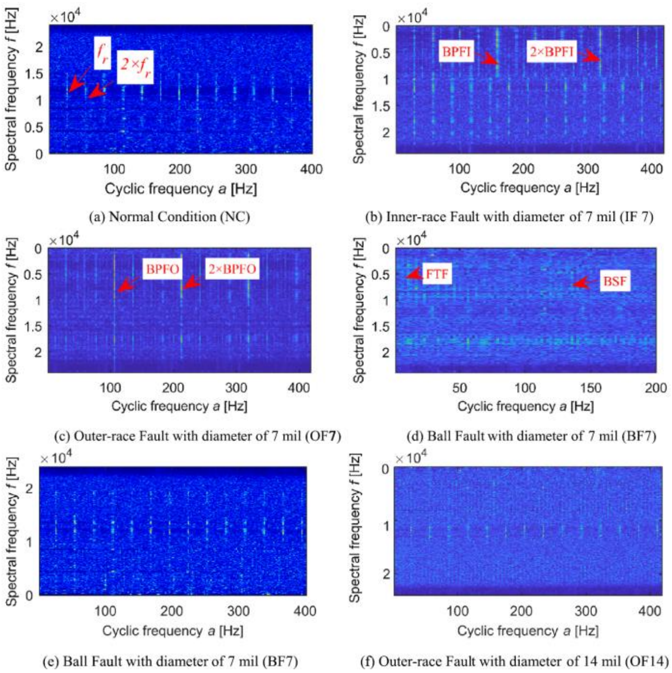

FIGURE 3. The 2D CSCoh maps of the different bearing health conditions.

D. DATA AUGMENTATION TECHNIQUE

In consideration of the gradual architecture complexity and increasing parameters optimization of CNN, the quality of required training data becomes more massive accordingly. In order to enhance the generalization performance and classification accuracy of CNN, data augmentation method has been utilized to expand training datasets [98,99].

By the use of data augmentation strategy based on Gaussian white noise via MatLab software, a typical CNN was employed to classify simulated ovalization fault data of journal bearings [100]. The augmented datasets were fed into the established model, including training dataset with a proportion of 50%, 25% of validation dataset and testing dataset respectively, as depicted in Figure 4.

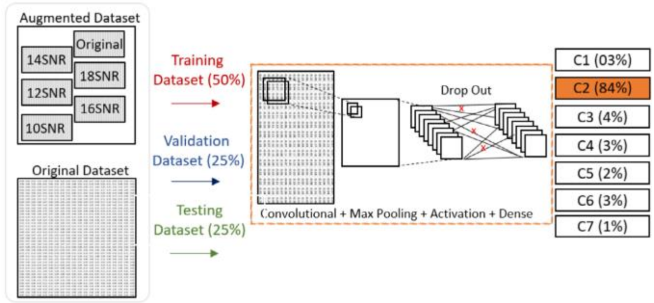

FIGURE 4. Ovalization fault diagnostics framework with CNN.

Owing to the reception of the directly raw vibration signals without image transformation, 1D CNN has been used to machinery fault detection and diagnosis [87,101]. A new 1D CNN was proposed to diagnose bearing fault in interferential environment and varying workload, with no need for additional denoising operation and domain adaptation strategies. It should be pointed out that a convenient data augmentation method was adopted to preprocess the training samples to meet the requirements of constructed CNN. The specific procedure was presented in Figure 5. Similarly, the data augmentation of overlap was used as well by Chen et al [102]. Previously, the raw vibration signals are acquired in both the horizontal and the vertical directions. Finally, a 1D CNN was developed for fault diagnosis of planetary gearbox, vibration data as input in the form of time series.

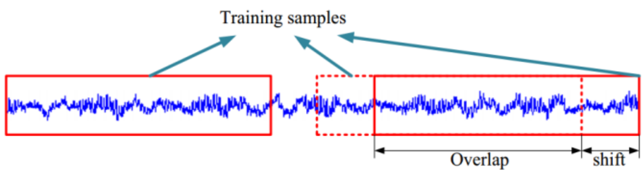

FIGURE 5. Data augment with overlap.

The number of raw vibration data was firstly increased via augment tricks of shift stride. Before classification operation was performed with constructed CNN model, the augmented raw vibration signal was converted into gray-scale images with a new signal processing strategy, as depicted in Figure 6 [103,104,105].

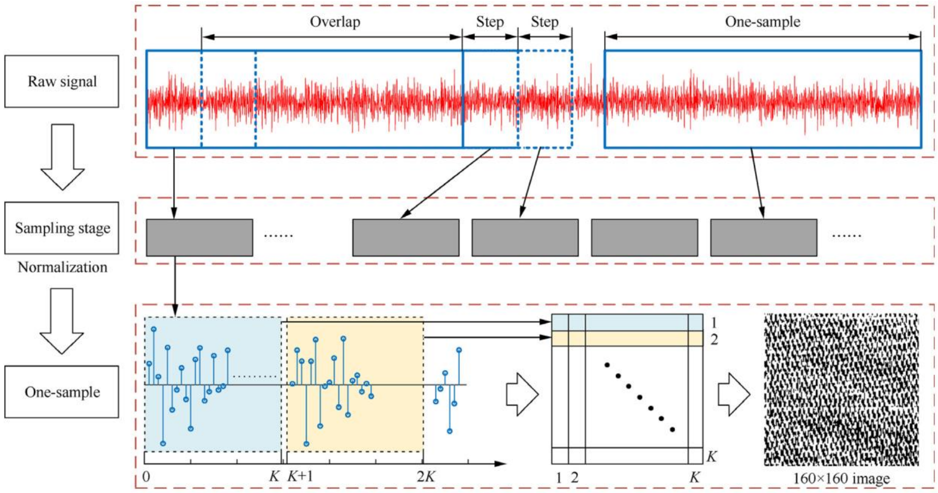

FIGURE 6. Signal-to-image conversion process.

A signal generally consists of signal component with multiple frequency components. A trend term is often generated in the process of signal acquisition. The trend term refers to the frequency component in the signal whose period is longer than the sampling length. A de-trend signal can be understood as the signal component in which the signal component with the trend component has been removed. With an integration of de-trend signal, instantaneous angular acceleration and instantaneous angular speed, Jiao et al. proposed a multi-information fusion method to preprocess data. The constructed CNN was employed for fault diagnosis of planetary gearbox, data segmentation as a way of data augmentation [106].

With the moulding and imaging method, 2D mould images were obtained by optical microscopy [107]. Then the acquired images were augmented with the cropping and in-plane rotation approach, which made preparations for subsequent network input [108].

E. OTHER TECHNIQUES

There are many data preprocessing methods and some methods have been successfully applied to common machinery fault diagnosis. However, the approaches used for intelligent fault diagnosis are limited, especially for the CNN based intelligent fault diagnosis. Recently, the methods are primarily wavelet transform, S-transform, cyclic spectral coherence and data augmentation used in the CNN based intelligent fault diagnosis for rotary machinery. The applications of other methods are relatively lacking. The fast Fourier transform was employed to accomplish the transformation of the vibration signals in different time segments into spectral image (Figure 7). Through such primary treatment, the obtained 2D images was fed back to the CNN for bearing fault diagnosis [109].

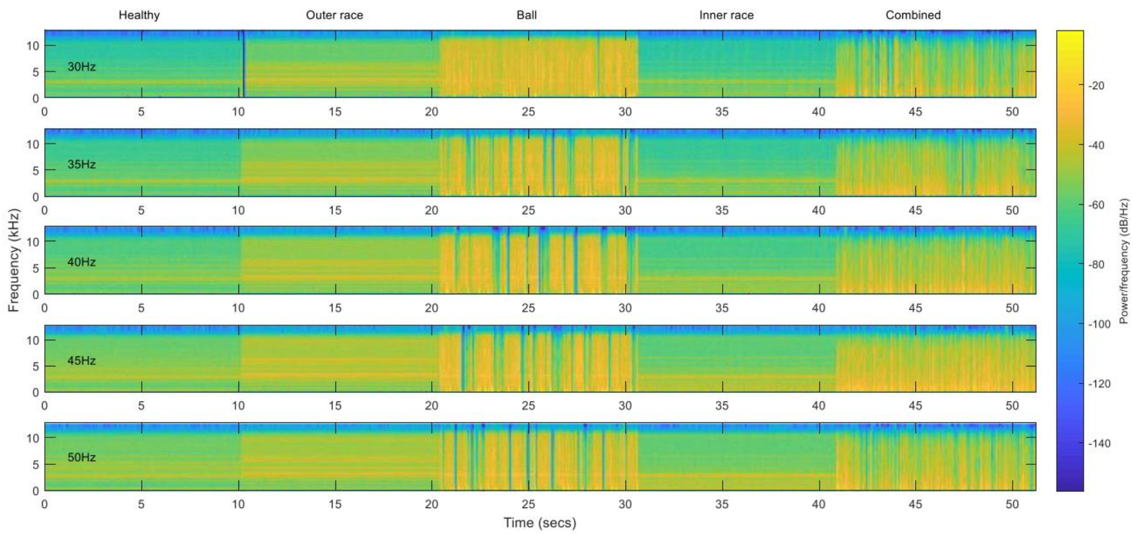

FIGURE 7. Spectrograms of the raw vibration data for different operating conditions under different speeds.

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Zhao et al. developed a new framework called local global deep neural network algorithm, with FFT processing the acquired vibration signal [110]. As shown in Figure 8, the Fisher parameter optimization criterion was introduced to realize the differentiable feature extraction, which was the key point in the proposed architecture.

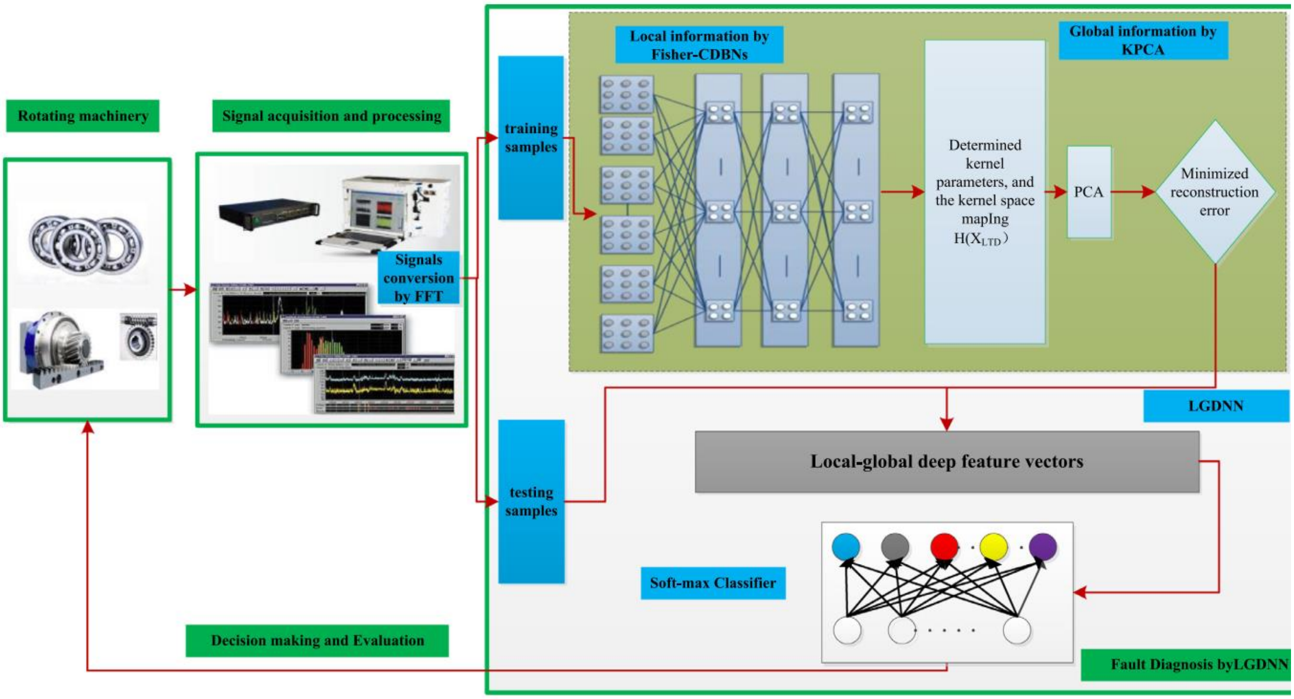

FIGURE 8. The flowchart of rotating machinery fault diagnosis method based on LGDNN. LGDNN represents the local-global deep neural network.

Symbolic analysis could acquire probability distribution from original time series data and is capable of interpreting nonlinear dynamics of system in rotating machinery [111,112]. The basic flowchart was displayed in Figure 9. In the light of the disadvantages of entropy-based methods in both the interference and potential overlaps of probability vector, symbolic analysis was employed to the extraction of probability vector from original signals. Hierarchical symbolic analysis was introduced by Yang et al. to accomplish the preliminary feature extraction via the pretreatment of raw fault data. And then a CNN framework was constructed to classify the fault towards centrifugal pump and motor bearing [113].

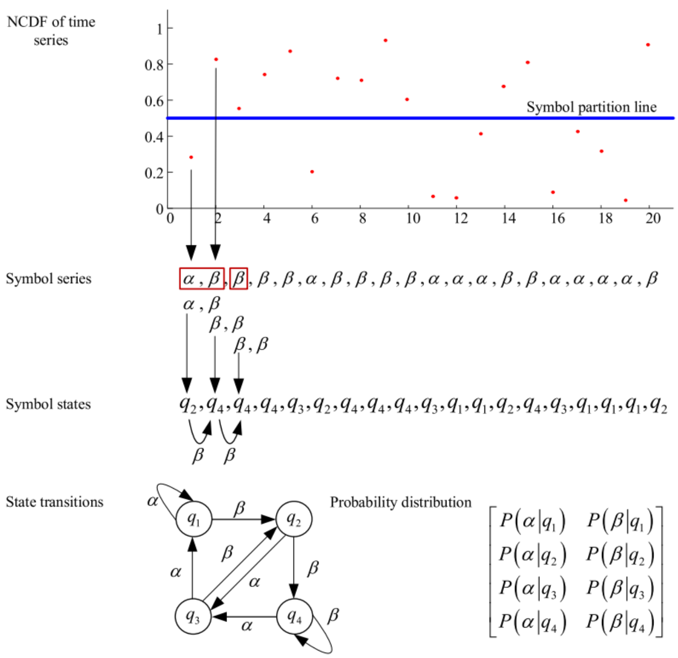

FIGURE 9. The flowchart of symbolic analysis. NCDF represents the normal cumulative distribution function.

IV. CONCLUSIONS AND PERSPECTIVES

Data preprocessing has been studied in many conventional fault researches, which provides valuable reference for the applications in intelligent fault diagnosis [114,115,116]. Intelligent fault diagnosis based on CNN has made some progress in rotating machinery, leveraging the strengths of CNN in automatic learning [117,118,119]. In consideration of the limitations of practical equipment operation, it is difficult to collect sufficient real fault data. In order to satisfy the input requirement of 1D CNN, data augment makes it available to obtain a large amount of data. With respect to the 2D CNN based methods, 2D image is required as input, which requests such preprocessing operation as transformation of raw data. Through the analysis of the recent data preprocessing in CNN based diagnostic approaches, many studies pay attention to the single preprocessing method. There are few researches on the contrastive analysis and optimization of preprocessing methods. Moreover, very few are concentrated on the potential mechanism of enhancement in regard to the constructed methods and eventual diagnostic performance.

In the future research, fusion methods will take the advantage of individual method may be more effective and desirable. On the basis of the superiority of 2D CNN, raw data could be converted into images and further data augmentation will gain sufficient data for training of network. It is advantageous to decrease the learning difficulty of CNN and eventually achieve the enhancement of diagnosis accuracy. Furthermore, it will be an underlying research direction to exploit novel preprocessing algorithm to afford the admirable input of CNN.

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