Fault Diagnosis of Wind Turbine Drive Train using Time-Frequency Estimation and CNN

Jing Li
School of Information Engineering
Nanjing Audit University
Nanjing Jiangsu China
230149053@seu.edu.cn

Aidong Deng†
National Engineering Research Center of Turbo-generator Vibration
Southeast University
Nanjing Jiangsu China
dnh@seu.edu.cn

Yong Yang
School of Information and Electrical Engineering
Xuzhou College of Industrial Technology
Xuzhou, China
yongyang@cumt.edu.cn

Qiang Cheng
National Engineering Research Center of Turbo-generator Vibration
Southeast University
Nanjing Jiangsu China
cq_njust@qq.com

***Abstract*—Based on the rapid development of wind power, drive train monitoring system is designed to determine the health of wind turbine and to reduce the operating costs by allowing a predictive maintenance strategy. This paper presents a novel method of fault detection using vibration signal. The method is composed of two steps. First, the Wigner Ville Distribution with window function is used to extract time frequency feature from every acquired signal. Then, the convolutional neural networks served as tracking detection model is applied on all available time frequency feature. The spectral peaks and the spectral structures are constantly learned, which are utilized to generate the diagnosis system of drive train. The proposed method is tested on signals from a drive train of wind turbine test rig. Experiments indicate that the proposed recognition algorithm is an effective way to diagnosis the faults between gearbox and rolling bearing.** *(Abstract)*

Keywords: drive train of wind turbine; Wigner Ville Distribution; convolutional neural networks

I. Introduction

Energy is the cornerstone of human survival and development. Under the dual background of sustainable energy development and severe environmental problems, wind energy, as an inexhaustible renewable and clean energy, has received high attention worldwide in recent decades [1-2]. With the rapid development of wind power, the operation fault of wind power unit has become the focus of attention. The occurrence of wind turbine faults not only seriously affects the generation capacity, but also greatly increases the maintenance cost of wind farms and seriously damages the economic benefits of wind farms. Therefore, it has become a major and urgent research topic for wind power industry to accurately warn the signs of faults, closely monitor the development of faults and take timely measures to avoid the occurrence of major equipment faults.

Wind turbines working at all-weather running alternating load condition and their complex structure of drive train make fault diagnosis in trouble. The drive train of wind turbines is combined by several machinery components including: bearing, gearbox, shaft and so on. The main failure forms include gear pitting, crack, broken teeth, tooth surface wear, cage damage, shaft imbalance and shaft bending. In addition, theses faults often affect each other presenting coupling characteristics. Be consistent with above faults, fault diagnosis methods mainly including vibration analysis, oil analysis, noise detection, nondestructive testing. Vibration signal analysis is most commonly used to detect faults in rotating machinery based on the theory and method of the mechanical dynamics. It involves two main methods including dynamic analysis and data-driven model method. Due to complicated working environment, it is very difficult to accurately analyze its dynamics characteristics. However, the data-driven model can keep away from these problems and build the model to realize fault diagnosis of components from the sensor data collected in real time [3-5].

Time-domain analysis and frequency-domain analysis are the two main processing method to calculate some typical time-domain and frequency-domain statistical characteristic parameters, which have the advantages of convenient calculation and clear physical significance of characteristic parameters [6-8]. However, considering the complexity, strong non-linearity, uncertainty of operation condition and strong background noise of mechanical equipment, the time-frequency analysis method can obtain the time-frequency domain energy distribution, image texture, information entropy and other characteristics of the signal, which can better describe the nonlinear and non-stationary characteristics of fault vibration signal of rotating machinery [9-12].

Short-time Fourier Transform (Short Time Fourier Transform, STFT) as from the perspective of Time domain and frequency domain analysis of the pioneer of fault signal is to let the signal we have a better cognition, but when using STFT analysis of non-stationary signal, STFT is limited by Heisenberg's uncertainty of the rule, not balancing the needs of temporal resolution and frequency resolution window function, the area of the time-frequency window cannot be less than 2, therefore, cannot satisfy two resolution at the same Time.

Compared with STFT, the window function of Wigner Ville Distribution has good temporal resolution and frequency resolution, and is superior to STFT in reflecting signal clarity. The time-frequency bandwidth product of WV distribution reaches the lower bound given by the Heisenberg uncertainty principle, which enables it to have a high time-frequency resolution without losing the amplitude and phase information of the signal, and has a good time-frequency expression ability for non-linear and non-stationary signals.

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Recognition model is the key part to transform features into diagnosis results [13-15]. Several types of neural network model, such as the Radial Basis Function Neural Network, Self-organizing Mapping Neural Network, Multi-layer Perceptron Neural Network, and Back Propagation, etc. have been widely used in the field of gearbox fault diagnosis and achieved good results. As the deep learning technique keeps going, some novel fault diagnosis models different from traditional machine learning frameworks are gradually coming to the fore, such as convolutional neural networks (CNN), recurrent neural networks, deep belief networks and so on. In recent years, CNN has also been applied massively in image processing [16-19].Compared with the image processing, the time-frequency image carries lots of time and frequency features in the way of images. It makes full use of the capacity of CNN model to detect faults in rotating machinery without human intervention.

In this paper, a novel framework of fault diagnosis used in wind turbine drive train is proposed. Two views of information features are adopts to completely express faults characteristics in time frequency domain. CNN model could be utilized to remove the interference information and dig out the target features by self-learning. The experiment proves its superior performance on different components condition diagnosis of wind turbine transmission test bed. The rest of this paper is organized as follows. Section 2 introduces WV distribution algorithm. In Section 3 it introduces test bad and waveform characteristics in different components and states. In Section 4 it introduces results of experiment and final conclusions.

II. WIGNER-VILLE DISTRIBUTION

In the process of signal processing, the Wigner Distribution Function is very good for analyzing many unsteady random signals, especially in the fault diagnosis of wind turbine drive train. Assuming that the Fourier transform of signal $x(t)$ and $y(t)$ is $X(\mathrm{j}\Omega)$ and $Y(\mathrm{j}\Omega)$, the Wigner Distribution Function of $x(t)$ and $y(t)$ is defined as:

$$W_{x,y}(t,\Omega)=\int_{-\infty}^{+\infty}x(t+\tau/2)y^*(t-\tau/2)e^{-j\Omega t}d\tau \tag{1}$$

The Wigner Distribution Function of the signal $x(t)$ itself is defined as:

$$W_x(t,\Omega)=\int_{-\infty}^{+\infty}x(t+\tau/2)x^*(t-\tau/2)e^{-j\Omega t}d\tau \tag{2}$$

Where x^* and y^* are the complex conjugate of $x(t)$ and $y(t)$ .In equations (1) and (2) the integration should be carried out on the whole sampled time. However, in practical applications it is difficult to carry out. Therefore, it is necessary to carry out discrete processing of signals and solve the problem of finite length of data. The implementation process is as follows:

$$W_{\mathrm{x}}(t,\Omega)=\sum_{\tau=-\infty}^{+\infty}r_x(t,\tau)e^{-2j\Omega\tau}$$

$$r_x(t,\tau)=x(t+\tau/2)x^*(t-\tau/2) \tag{3}$$

In the above equation, the $r_x(t,\tau)$ is depended on time t which is named instantaneous autocorrelation. Time discretization results in frequency periodization. Ordinarily, after time discretization, frequency periodization of $x(t)$ could be 2π . However, the above kernel function is $e^{-2j\Omega\tau}$, which makes the frequency periodization transform into π . If it samples as Shannon Sampling Theorem $f_s=2f_{\max}$, the changed frequency periodization will produce serious signal aliasing problem. To solve this problem, the related improved methods have been proposed including analytical signal after Hilbert transform, interpolation of $x(t)$ and smooth window of signal and so on.

Then, the paper proposed adding window function to process the signal $x(t)$ because the Hamming window can improve the spectrum releasing conditions as showing in following.

$$w(n)=\begin{cases}0.54-0.46\cos[2\pi n/(N-1)], & 0\le n\le(N\text{-}1)\\ 0, & \text{others}\end{cases}$$

(4) The WV result is:

$$W_{\mathrm{x}}(t,\Omega)=\sum_{\tau=-\infty}^{+\infty}g(\tau)r_x(t,\tau)e^{-2j\Omega\tau} \tag{5}$$

Where $0\le\tau\le N-1$, $g(\tau)$ is the window function, $W_{\mathrm{x}}(t,\Omega)$ is the Pseudo Wigner Ville (PWV). According to time marginal property, the WV signal integrals along the frequency axis, which could be equivalent to the instantaneous energy of the signal at time t.

$$\frac{1}{2\pi}\int_{-\infty}^{+\infty}W_{\mathrm{x}}(t,\Omega)d\Omega=|\boldsymbol{x}(t)|^2 \tag{6}$$

Also According to frequency marginal property, the WV signal integrals along the time axis, which could be equivalent to the instantaneous energy of the signal at frequency f.

$$\int_{-\infty}^{+\infty}W_{\mathrm{x}}(t,\Omega)dt=|\boldsymbol{x}(\Omega)|^2 \tag{7}$$

Thus, the WV signal shows instantaneous energy distribution property from frequency and time domain views.

III. WAVEFORM CHARACTERISTICS ANALYSIS

Drive train of doubly-fed wind turbine is usually made up of gearbox, bearing and main shaft and so on. Faults of wind turbine drive train mainly occur in gearbox and bearing. Vibration signal analysis served as a powerful tool, characteristic frequency usually refers to gear meshing frequency, shaft frequency and bearing inner and outer ring frequency and rolling body frequency. Gear meshing frequency refers to the number of gears multiplied by the rotation frequency. Failure frequency of bearing inner ring is shown in the formula below:

$$f=\frac{1}{2}f_r z(1+\frac{d}{D}\cos\alpha) \tag{8}$$

Where f_r the rotation frequency of the shaft, z is the number of rolling bearings, d is the ball diameter, D is the bearing diameter and α is the bearing contact angle.

To simulate wind turbine drive train, test bed in laboratory is consist of rolling bearing, cylindrical gearbox, planetary gearbox and drive motor and so on. Among these, cylindrical gear and rolling bearing as the object, through artificial preparation of cylindrical gear tooth break fault and roller bearing inner ring crack failure of 0.8 mm as shown in following pictures.

(a) Broken tooth (b) Boller bearing crack failure

Figure1 Failure description.

Cylindrical gearbox and rolling bearing operate under normal and fault conditions at 1000r/min and 40r/min respectively. Figure2- Figure 5 are vibration waveforms of gear box and rolling bearing at a certain time at 16,384 points continuously collected by the lower computer acquisition system at 16 sampling cycles.

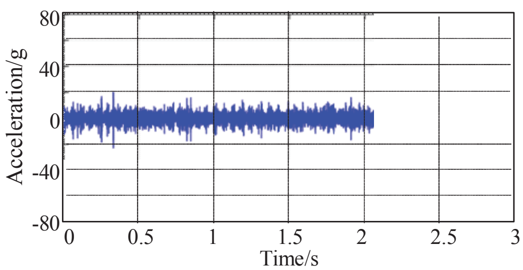

Figure2 Waveform of gearbox in health condition.

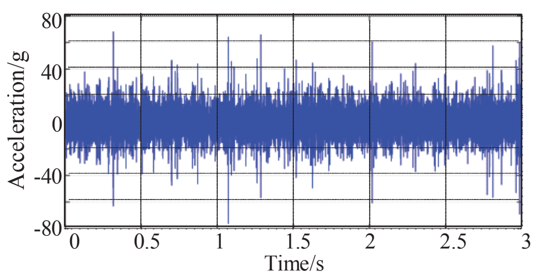

Figure3 Waveform of gearbox in fault condition.

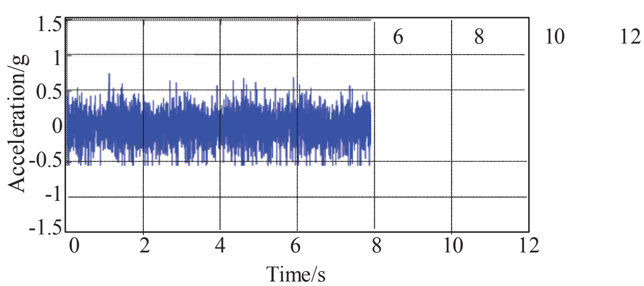

Figure4 Waveform of bearing in health condition.

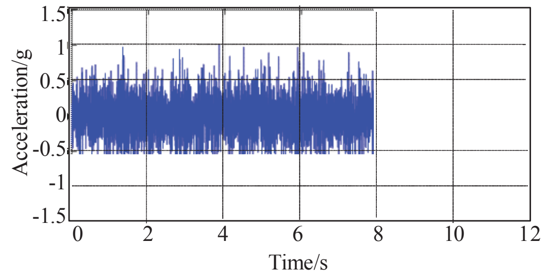

Figure5 Waveform of bearing in fault condition.

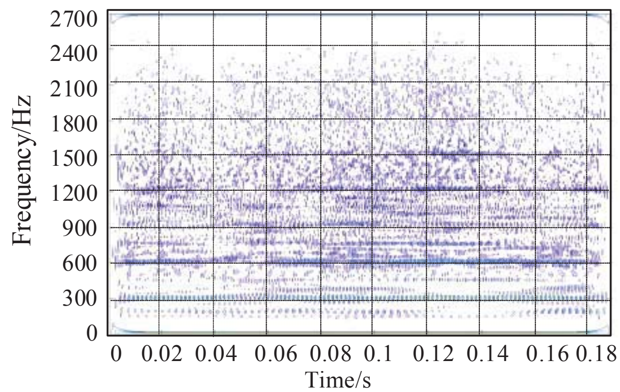

Figure6 WVD of gearbox in health condition.

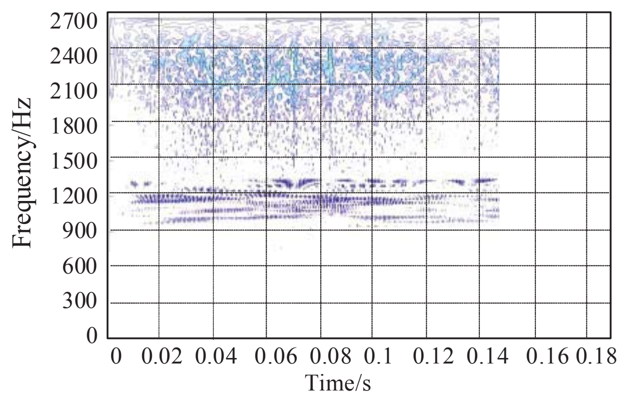

Figure7 WVD of gearbox in fault condition

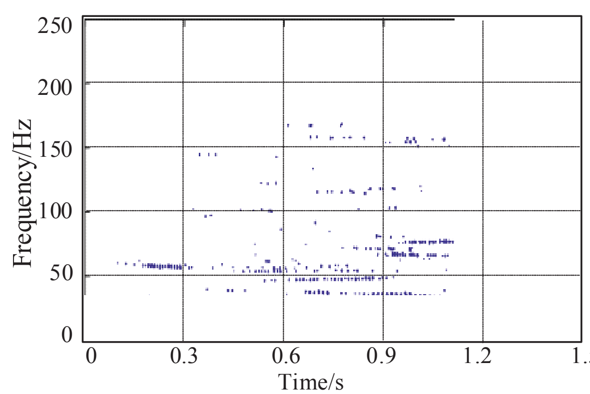

Figure8 WVD of bearing in health condition.

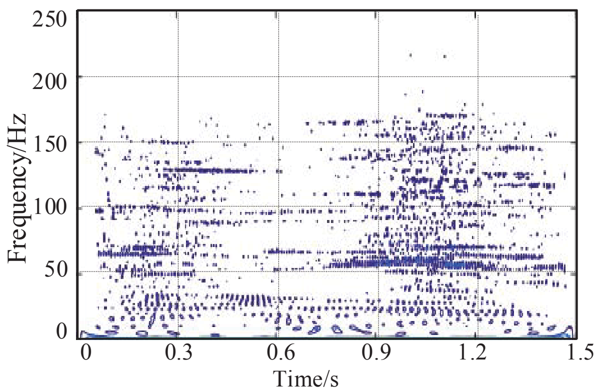

Figure9 WVD of bearing in fault condition

And then use the WV distribution algorithm and time synchronous averaging method to extract the cylindrical gear and rolling bearing of time-frequency spectrograms, and then on the basis of time-frequency figure judging cylindrical gear box and the running state of rolling bearings.

Figure6 and Figure7 respectively present the WVD of cylindrical gearbox in health and fault conditions. The number of small teeth of cylindrical gears is 18 and the rotational speed is 1000r/min, where the meshing frequency could be calculated approximately to 300Hz. Meshing frequency and its harmonic frequency can be obviously seen in Figure6 due to each impulse at every teeth meshing. Every time the fault cylindrical gear impacts with the broken tooth. The vibration signal caused by this impact contains short-time high-frequency components. The frequency of the gear meshing caused by the broken tooth is modulated by the fault frequency, resulting in the amplitude of high-frequency components becoming significantly increasing. According to this case, Figure7 presents abundant high-frequency components in WVD. By contrast, Figure8 and Figure9 present the WVD of rolling bearing in health and fault conditions. The rotational speed is 1000rad/min, where the feature frequency is 39.38Hz. Figure8 presents much cleaner WVD than Figure9. It is the most likely that feature and its harmonic frequency of inner ring crack fault have been modulated by rotational frequency. Thus, the frequency components are abundant from 0Hz to 175Hz.

IV. EXPERIMENT ANALYSIS

Based on the calculated WVD features, the fault recognition model are constructed by the deep learning architecture of CNN as shown in Figure 10. It mainly divides into four parts including the input layer, two convolution layers and two sampling layers, the whole connection layer and output layer. Considering WVD with 1024 × 1024 dimensions, two convolution layers respectively use convolution kernels $64@256\times256$ and $128@64\times64$, and two sampling layers respectively use the average processing method with $64@2\times2$ and $128@2\times2$. Then output layer used softmax nonlinear activation function to detect faults.

Time-frequency diagram as input features, and then two convolution and sample layer appear alternately, /and/respectively, and the characteristics of figure screening using the average processing method (namely/area average), after two sampling and convolution using sigmoid nonlinear activation function, finally all connections and output layer form a Softmax classifier.

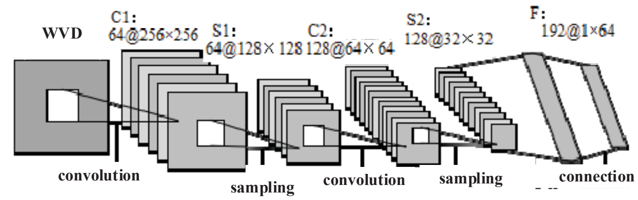

Figure10 recognition model structure

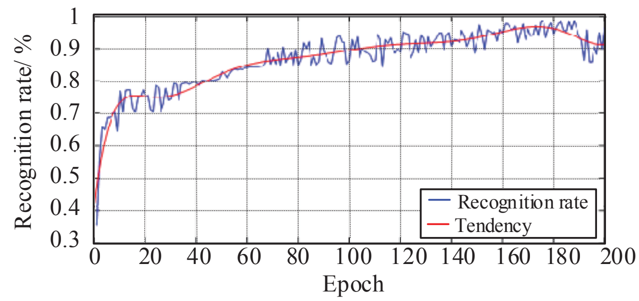

Figure11 Recognition results of different epochs.

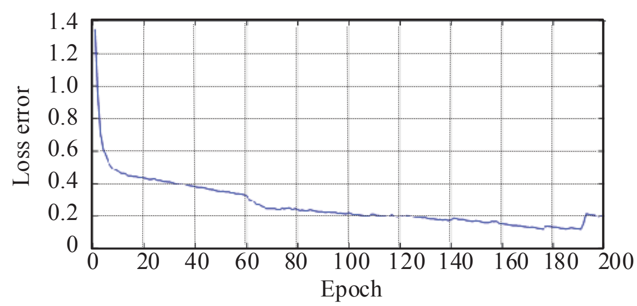

Figure12 Recognition results of different epochs

The test adopts training parameters including batch=32, epoch=200, learning rate a=0.0002, using the optimizer of Adam algorithm, and cross entropy as the error function. Figure 11 and Figure 12 show the error curve in the network of training process, where the horizontal axis represents the training process of 200 iterations for all batch samples, and the vertical axis represents the fault recognition rate and error value of each iteration respectively. It can be seen from the figure that after 120 iterations of network training, the error value tends to a smaller value, indicating that the network has trained to convergence.

TABLE I. THE CONFUSION MATRIX OF RECOGNITION RESULTS

	Health	**Broken tooth**	**Bearing inner ring crack**
Health	100%	0	0
Broken tooth	0	97.78%	2.22%
Bearing inner ring crack	0.52%	8.81%	90.67%

It is a confusion matrix for vibration signal identification of gear box gear failure and rolling bearing failure using WVD features and CNN model. Among them, the recognition rate of broken tooth fault of cylindrical gear box is higher, reaching 97.78%. The fault identification rate of rolling bearing inner ring is 90.67%. The experiment shows that the CNN model can be used to identify the characteristics of the time-frequency diagram of the WV distribution of the vibration signal.

V. CONCLUSION

This paper presents a novel fault detection method of wind turbine drive train based on vibration signal. The method is composed of two steps. First, the Wigner Ville Distribution is used to extract time frequency feature from every acquired signal. Then, based on the spectral peaks and the spectral structures, the convolutional neural networks served as detection model is applied on all available time frequency feature. The presented method is tested and validated on the acquired signals from wind turbine test rig. Experiential results indicate that the proposed recognition algorithm could effectively capture the characteristics of different faults between gearbox and rolling bearing. It is an effective way to diagnosis the health condition of wind turbine.

VI. CONFLICT OF INTERESTS

The authors declare that there is no conflict of interests regarding the publication of this paper.

VII. ACKNOWLEDGEMENTS

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