

Time-frequency Analysis for Validating Prognostics Algorithms of Rolling Element Bearings

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Abstract—This study employed the time-frequency analysis to compute some of the XJTU-SY bearing datasets and aimed at the investigation of spectrogram of the raw data of the datasets. The methods of this study are divided into 4 parts: (1) spectrogram, (2) XJTU-SY bearing datasets, (3) equipment and, (4) 2D correlation. The results show the dominant reasons of malfunction of the machine occur in the duration of the 75th to 100th minutes. Both 2D correlation coefficients of the spectrograms of horizontal and vertical vibrations in the 100th and 123th minutes are larger than 0.8 because rotation of the roller entered a distinguished state of malfunction in the 100th minute. The inner damage is enhanced step by step. The interpretation of VEs and HEs is helpful to detect the fault diagnosis of the roller. The further studies will test more data, and add more algorithms for the accurate diagnosis.

Keywords—XJTU-SY bearing datasets, spectrogram, correlation coefficient, episode, roller

I. INTRODUCTION

This study employed the time-frequency analysis to compute some of the XJTU-SY bearing datasets which are supported by the Institute of Design Science and Basic Component at Xi'an Jiaotong University (XJTU), Shaanxi, P.R. China and the Changxing Sumyoung Technology Co., Ltd. (SY), Zhejiang, P.R. China [1]. Time-frequency analysis owns the benefits of obvious presentation of the fundamental and harmonic components of a segment of a signal. Therefore, some problems of the rolling elements can be detected by this analysis because of the periodic touches in the disorder place of the rotation of the roller. Therefore, we propose the method of time-frequency analysis to be the pre-processing for validating prognostics algorithms of rolling element bearings.

Prognostics and health management (PHM) is very helpful to (1) ensure the safe operation of machinery, (2) improve the

productivity, and (3) increase economic benefits [2]. Many studies employed the XJTU-SY bearing datasets to explore the feasibilities of the aforementioned 3 categories of performances. For example, Wu et al. have developed a hybrid deep-learning model based on CNN and gcForest [3]. Yao et al. proposed a method using the ability of the 1D-CNN to extract signal features of the signals in the XJTU-SY bearing datasets [4]. Zhao et al. [5] proposed a method of the signal-to-signal translation into the field of data-driven fault diagnosis of bearings and gears. The performance and excellences of the proposed method are displayed in the accuracy of detections. The signal-to-signal translation is a feasible solution. Furthermore, the DL-based fault classification models in Zhao et al.'s study present the better performance on the four public datasets. Yang et al. proposed a classical fuzzy C-means method was used to classify the fused signals from the model [6]. Gao et al. employed many statistical approaches to explore the dataset. They improved the accuracy because time-domain features were extracted from the bearing vibration signal as well as Bayesian model of state parameters and bearing life is established [7]. Ma et al. used the method of multistep dynamic slow feature analysis [8]. The results shows that the interpretability of the fault information based on five monitoring indicators and the detection rate of unsteady process are improved.

However, the applications of time-frequency analysis were widely used in many fields, such as lung sound diagnosis [9–11] and speech recognition [12–14]. Furthermore, spectrogram is a very crucial tool to display the results of time-frequency analysis. Therefore, some studies related to the XJTU-SY bearing datasets were inserted spectrograms as a method for analysis. Zhang et al. employed the data of spectrogram as an input of improved ConvNext[15]. Cheng et al. compared the spectrograms between trained and untrained data {16}. The function of spectrogram supported an efficient method to the studies.

Our study aimed at the investigation of spectrogram of the raw data of the XJTU-SY bearing datasets. Because of the physical factors of the rotation of the roller, a direct observation of spectrograms must show some findings to explain the fault diagnosis by the computation through the XJTU-SY bearing datasets.

II. METHODS

The methods of this study are divided into 4 parts: (1) spectrogram, (2) XJTU-SY bearing datasets, (3) equipment and, (4) 2D correlation. The 3 parts are described as follows:

A. Spectrogram

The element $x[n]$ at the point of time n in a spectrogram is defined as (Haykin, Van Veen, 1998),

$$|X_r(j\Omega)|^2 = \left| \sum_{n=-\infty}^{\infty} x(n) w^*(n-\eta) e^{-j\Omega n} \right|^2 \quad (1)$$

where $w^*(n-\eta)$ is a Kaiser window function which is defined as:

$$w(n) = \begin{cases} \frac{I_0\{\beta[1 - (\frac{n-\eta}{L})^2]\}}{I_0(\beta)} & n = 0, 1, 2, \dots, L \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

where $\eta = (L-1)/2$ and I_0 is the zeroth-order modified Bessel function of the first kind. When $\beta = 0$, the Kaiser window becomes a rectangular window, as well as, when $\beta \geq 0$ parameter allows for a trade-off between side lobe amplitude and main lobe width. In this case, $L=500$ and $\beta = 5$. The operator $e^{-j\Omega n}$ is the same to discrete Fourier transform (FFT) as a phasor operation. The spectrogram presents the relationship of the magnitude (in dB) of time-independent discrete Fourier transform v.s. time. The number of a frame for short FFT is 512, and the number of overlapped pints is 475. The sampling frequency of the explored signals is 25600 Hz. The computation compiled in MATLAB 7 (MathWorks, USA) development environment.

B. XJTU-SY bearing datasets

In this study, we focused on Bearing1_1 whose conditions are 123 files, 2 hours and 3 minutes lifetime, and the fault element of outer race in the XJTU-SY bearing datasets. In a file, there are individually 32768 points in horizontal and vertical sensing, and the sampling frequency is 25600 Hz. Therefore, the length of the record in a file is 1.28 seconds. The data record occurred at the beginning of 1.28 seconds in every minute.

C. Equipment

The type of tested bearings is LDK UER204 which has been described in reference [1] in details.

D. 2D correlation coefficient (r)

The equation of 2D correlation coefficient of the two arrays, A_{mn} and B_{mn} , can be written as:

$$r = \frac{\sum_m \sum_n (A_{mn} - \bar{A})(B_{mn} - \bar{B})}{\sqrt{(\sum_m \sum_n (A_{mn} - \bar{A})^2)(\sum_m \sum_n (B_{mn} - \bar{B})^2)}} \quad (3)$$

where the average of the elements in A_{mn} is denoted by $\bar{A}$, and the average of the elements in B_{mn} is denoted by $\bar{B}$.

III. RESULTS

A. Spectrograms

The recorded signals and corresponding spectrograms in the 1st, 25th, 50th, 75th, 100th, 123th minutes are shown in Figs 1 to 6. The left sides are the horizontal vibrations, and right sides are the vertical vibrations.

In Fig. 1, there are some unclear vertical episodes (VE). It means some little pulses of pressure detected. Then, the number of VE increases in Fig. 2. In addition, the VE is much ably visual in the range of higher frequency in the spectrograms. The looks of Fig. 2 and Fig. 3 are very similar. However, the looks between Fig. 3 and Fig. 4 are different in vertical vibrations. Sequentially, the looks of Fig. 4, 5, and 6 are much different one another. Especially, in Fig. 6, the VEs are obviously increasing in the range of the low frequency.

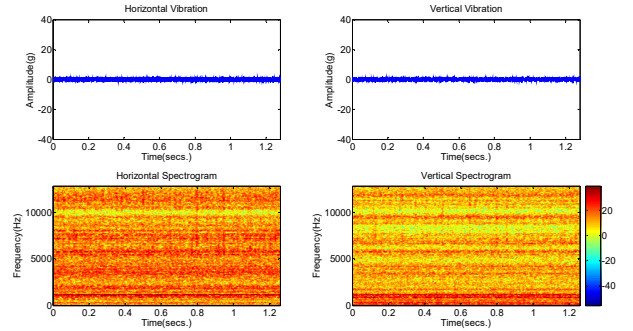


Figure 1. The recorded signals and corresponding spectrograms int the 1st minute.

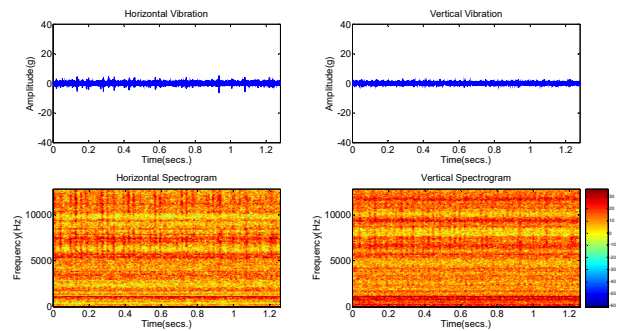


Figure 2. In the 25th min.

B. 2D correlation coefficients

To check the similarities of the spectrograms in Figs 1 to 6, we compute the r of spectrograms one another in horizontal and vertical vibrations, respectively. The results are shown in Tables 1 and 2. The r of horizontal and vertical vibrations are presented in Table 1 and Table 2 as well as denoted by r_h and r_v , respectively. In the 2 tables, A is the index of the column and B is the index of the raw. The indexes are the time point

in minutes of 1st, 25th, 50th, 75th, 100th, and 123th, i.e. the corresponding time points in Figs 1 to 6. For example, $r_h(1,25) = 0.4039$, and $r_h(25,50) = 0.3875$. Consequently, $r_v(1,25) = 0.5992$, and $r_v(100,123) = 0.8007$ in Table 2.

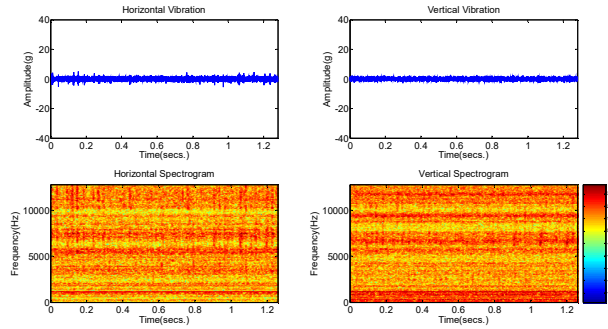


Figure 3. In the 50th min.

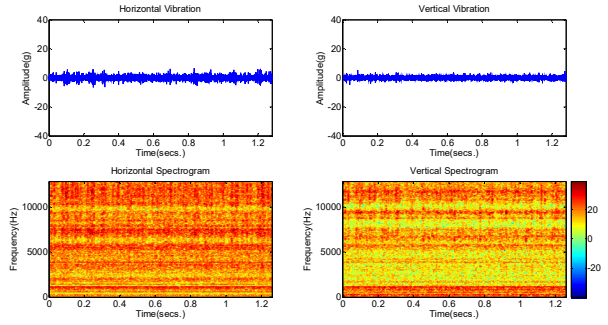


Figure 4. In the 75th min.

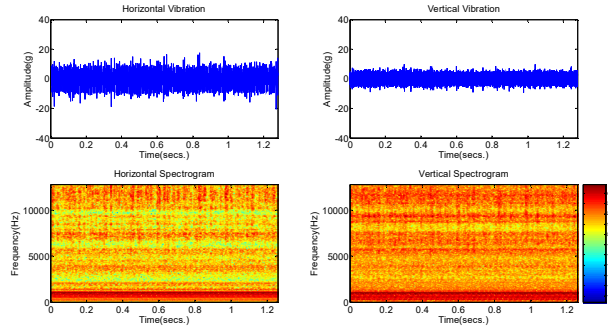


Figure 5. In the 100th min.

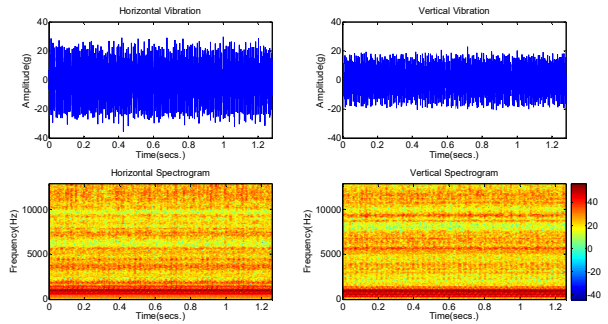


Figure 6. In the 123th min.

IV. DISCUSSION

In fact, Fig. 1 indicates that some weak pulse-like pressures have been detected, because the VE means the frequency

component of pulse waveform. The fundamental frequency in the spectrograms is near 250 Hz. The fundamental frequency can be ideally computed as:

$$f_o = f_r * N \quad (4)$$

Table 1 $r_h(A,B)$

$r_h(A,B)$	1	25	50	75	100	123
1	1.0000	0.4039	0.3504	0.2282	0.3115	0.2909
25	0.4039	1.0000	0.3879	0.3397	0.2136	0.1574
50	0.3504	0.3879	1.0000	0.3402	0.1923	0.1403
75	0.2282	0.3397	0.3402	1.0000	0.1633	0.0736
100	0.3115	0.2136	0.1923	0.1633	1.0000	0.8401
123	0.2909	0.1574	0.1403	0.0736	0.8401	1.0000

Table 2 $r_v(A,B)$

$r_v(A,B)$	1	25	50	75	100	123
1	1.0000	0.5992	0.5389	0.4346	0.4469	0.4765
25	0.5992	1.0000	0.5873	0.5155	0.3914	0.4266
50	0.5389	0.5873	1.0000	0.5100	0.3785	0.4070
75	0.4346	0.5155	0.5100	1.0000	0.3942	0.3756
100	0.4469	0.3914	0.3785	0.3942	1.0000	0.8007
123	0.4765	0.4266	0.4070	0.3756	0.8007	1.0000

where f_o and f_r denoted for fundamental frequency and rotating frequency in the operating condition, respectively. The number of ball is denoted by N . In this case $f_r = 35$ Hz, $N = 8$. Therefore, $f_o = 280$ Hz. The frequencies of harmonics are kf_o where $k > 1$ and k are integers.

In Fig. 2, the VEs are stronger; it indicates the collision in a pulse-like manner occurs. Therefore, the prediction of disorder can be made based on the phenomena at this time point. Figs 2 and 3 are similar so the rotation of the roller is stable in this duration, i.e. the 25th to 50th minutes. Possibly, it may span the stable duration to the 1st to 75th minutes. However, in the 75th minute, the spectrogram of the vertical vibration changes very obviously. The horizontal episodes (HE) reduced in the range of 1.5 to 5 KHz, i.e. the harmonics are weakening in the range in Fig. 4. Therefore, the status of rotation of the roller is not smooth as before in vertical direction. The damage in vertical direction occurs at first.

Sequentially, the investigation moves to Fig. 5. Compared with Fig. 4, all figures in Fig. 5 have huge changes. Both amplitudes of horizontal and vertical vibration signals are increased. In addition, the spectrogram of horizontal vibration shows the HEs become discontinuous, and VEs become much obvious. That is the pulses are strong, and the harmonics are not continuous. This releases a message to users that some impact forces occur in the machine. It is very possible to make the machine failure in a short time. In Fig. 6, the impact forces are much strong. The VEs are almost become vertical lines to be pure pulses in time domain in both horizontal and vertical vibrations. The inner damages of the machine disclose.

In Tables 1 and 2, the r of spectrograms one another in horizontal and vertical vibrations are displayed. To follow the sequential changes of spectrograms in Figs 1 to 6, two sequential sets are displayed in Fig. 7. One sequential set is $\{r_h(1,25), r_h(25,50), r_h(50,75), r_h(75,100), r_h(100,123)\}$ and the other is $\{r_v(1,25), r_v(25,50), r_v(50,75), r_v(75,100), r_v(100,123)\}$. Both $r_h(75,100)$ and $r_v(75,100)$ present the smallest values in

the sets. Therefore, the dominant reasons of malfunction of the machine occur in the duration of the 75th to 100th minutes. Furthermore, $r_h(100,123)$ and $r_v(100,123)$ are very high. Most textbooks deliver the concept of “If $r > 0.8$, the two data set are high correlation.” In Fig. 7, $r_h(100,123)$ and $r_v(100,123)$ are larger than 0.8 because rotation of the roller entered a distinguished state of malfunction in the 100th minute. The inner damage is enhanced step by step.

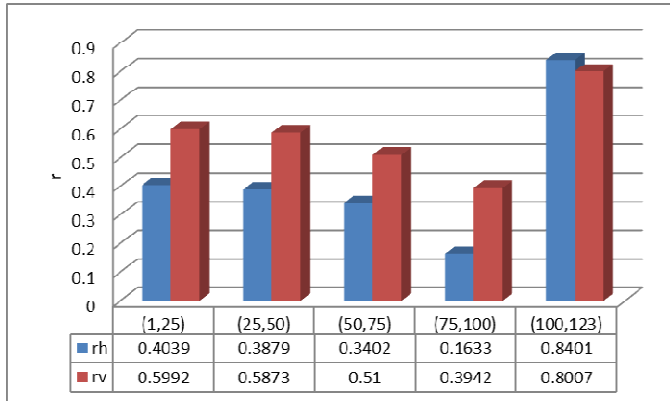


Figure 7. One sequential set is $\{r_h(1,25), r_h(25,50), r_h(50,75), r_h(75,100), r_h(100,123)\}$ and the other is $\{r_v(1,25), r_v(25,50), r_v(50,75), r_v(75,100), r_v(100,123)\}$.

V. CONCLUSION

The time-frequency analysis of Bearing1_1 of the XJTU-SY bearing datasets has been tried initially. The results present that the spectrogram-aided recognition is feasible. The interpretation of VEs and HEs is helpful to detect the fault diagnosis of the roller. The further studies will test more data, and add more algorithms for the accurate diagnosis.

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