Chapter

On-Line Monitoring and Intelligent Diagnosis Technology of Rail Transit Ventilation System

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Abstract

With the rapid development of economy and urbanization, subway has gradually become the main pillar of urban development. The ventilation system is the key guarantee of air quality in rail transit, and its condition monitoring and intelligent diagnosis are very important. The core problems of the complete set of a ventilation system required by the subway station have not been completely solved. The ventilation system includes the ventilator and additional equipment. The level of informatization and intelligence of the ventilation system and ventilator is not very high, and they have not yet been fully formed into an integrated diagnostic system. In view of the above two core issues, several scientific issues need to be tackled. This chapter studies the online monitoring and intelligent diagnosis mechanism of key equipment in the subway ventilation system. This mainly includes (1) modulation model of acoustic vibration signal; (2) noise reduction technology and feature extraction method; and (3) cases of multi-type typical fault identification fan equipment based on modulation model. Typical fault features were extracted respectively, which verified the effectiveness of the signal demodulation method for the diagnosis of rail transit ventilation systems.

Keywords: ventilation system, modulation model, feature extraction, fault identification

1. Introduction

With the rapid development of economy and urbanization, rail transit has gradually become the main pillar of urban development. However, the underground tunnel is a relatively closed space. On the one hand, the ventilation system is needed to ensure the ventilation of the underground space to ensure the supply of fresh air for personnel and normal operation of equipment. On the other hand, in case of fire and other major fire-fighting failures, the normal operation of the fan is required to ensure the timely discharge of harmful gases and the inhalation of fresh air.

At present, the core problems of rail transit ventilation system have not been completely solved. The ventilator and ventilation system have not been fully formed as an integrated diagnostic system yet. The degree of informatization and intelligence of the ventilation system is not high. In view of the above core issues, several issues need to be tacked.

Multi-sensor data fusion technology is the first issue. There are hundreds of monitoring points in the ventilation system, which contain various types of sensor data. Multi-sensor data fusion is a multi-channel signal acquisition system that realizes the data fusion, data storage, and real-time display of multiple signals.

Then, fault diagnosis, prediction, and processing technology is the second issue. Based on the data integrated by the multi-sensor data fusion technology, the features will be extracted by signal post-processing methods. In a general case, the extracted features could represent fault feature, which are used for fault diagnosis and fault prediction.

Finally, the platform for data analysis and management is the third issue, which combines the multi-sensor data fusion technology with the fault diagnosis, prediction, and processing technology. The platform mainly involves sensor network technology, intelligent acquisition and monitoring technology, and network intelligent diagnosis technology. The fault diagnosis technology of rotating machinery, which has an impact on the precision of fault detection, is essential to the realization of the intelligent diagnosis technology of the rail transit ventilation system. Therefore, the fault feature extraction method of rotating machinery signals has been widely studied [1].

For the monitoring signals of rotating machinery, the traditional Fourier transform spectrum analysis method obtains frequency domain information, but time domain information is lost. The frequency domain analysis method can accurately obtain the characteristic information for the steady-state signal of rotating machinery, but in the non-stationary state condition, time-frequency analysis (TFA) is an effective method for signal feature extraction. Many researchers have conducted extensive research on TFA, mainly including short-time Fourier transform (STFT), wavelet transform (WT) [2], Wigner-Ville analysis [3] methods, and so on.

STFT is a TFA method developed based on Fourier transform, which can obtain the time-domain and frequency-domain information of the signal, and can realize better characterization of the non-stationary characteristics of the signal [4]. WT is an improvement of STFT, which overcomes the limitation of time and frequency resolution of STFT [5]. In addition, WT is also an effective signal noise reduction method. Liu et al. used WT to estimate the variance of vibration and noise signals, so as to realize the noise reduction of monitoring signals [6].

In order to improve the readability of TFA results, many signal decomposition and analysis methods have been proposed. Common signal decomposition methods include singular value decomposition [7, 8] (SVD), empirical mode decomposition [9, 10] (EMD), local mode decomposition [11] (LMD), and ensemble empirical mode decomposition [12] (EEMD). For the feature components of multi-component fault signals obtained by signal decomposition, principal component analysis (PCA) can be used as an effective data dimensionality reduction and feature extraction method [13–15]. Rahmani et al. [16] have proposed an efficient PCA algorithm. Li et al. [17] used the PCA method to extract multi-sensor features of nuclear power devices to realize fault detection, fault recognition, and feature reconstruction. Prawin and Rama Mohan Rao [18] used the PCA method to reconstruct the online time series input force signal and realized the extraction of principal component features. However, the feature extraction method based on signal TFA cannot characterize the modulation information of rotating machinery and thus cannot directly obtain the low-frequency modulation information.

During the operation of rotating machinery, mechanical resonance will be caused by the excitation force. The broadband mechanical vibration caused by excitation force is the carrier of the modulated signal. Then, the feature frequency of low-frequency modulation can be extracted by demodulating the resonant frequency band. Therefore, the demodulation algorithm based on resonance frequency band has been widely studied. Envelope demodulation (ED), Kurtogram, Fast Kurtogram (FK), and Protrugram algorithms have been proposed successively, which are widely used in the extraction of fault features of rotating machinery or components [19]. Under the situations where the signal-to-noise ratio (SNR) is good, the spectral kurtosis (SK) analysis algorithm based on resonance narrowband signal demodulation can obtain better demodulation results. However, under the interference of strong non-Gaussian background noise, the SK analysis demodulation algorithm is easy to fail. When the SNR of the monitoring signal decreases, the demodulation and analysis performance based on the resonant frequency band decreases rapidly.

The demodulation method based on high-order statistics is an effective method to extract fault features of rotating machinery with high accuracy. It has better demodulation accuracy than the narrowband demodulation algorithm based on resonance band demodulation. Cyclostationary demodulation algorithm is a typical algorithm based on high-order statistics demodulation. Antoni and Randall [20] analyzed the relationship between correlation spectrum and envelope spectrum, and the research results show that correlation spectrum has better fault feature extraction accuracy. The analysis method based on second-order cyclostationarity is the most effective method to extract the fault information of rotating machinery from high-order statistics. Antoni [21] have carried out a detailed application research on the analysis method of cyclostationary signals, which have a good feature extraction effect on traditional rotating machinery.

In the research of rotating machinery demodulation algorithm, it is generally assumed that the noise interference signal is Gaussian white noise. Nevertheless, it is not consistent with many practical application scenarios. Borghesani et al. [22] carried out demodulation analysis and research on cyclostationary signals under non-white noise interference and proposed square envelope spectrum. However, the spectral correlation (SC) analysis algorithm has high computational complexity. Therefore, the SC analysis method cannot be effectively used to realize the online monitoring and fault diagnosis of rotating machinery. Antoni et al. [23] proposed a Fast-SC analysis method based on STFT, which was verified and analyzed by bearing fault experiments. Horstmann et al. [24] proposed the detection and identification of approximate cyclostationary signals and the estimation method of a cycle period. In the algorithm, signal resampling is the key technology. Sophie et al. [25] proposed to use the cyclostationary analysis method in the angle/time domain to identify the fault characteristics of the bearing housing under unsteady working conditions. The key is to use the encoder to collect the phase information and resample the time-domain fault vibration signal monitored by the rotating machinery. Borghesani and Antoni [26] analyzed the failure performance of square envelope spectrum and cyclic demodulation spectrum under peak background noise and further analyzed the effectiveness and anti-noise of logarithmic envelope spectrum by simulation analysis and experimental verification.

According to the research status of demodulation algorithm based on high-order statistics, although the demodulation algorithm based on high-order statistics can obtain better demodulation accuracy, its computational efficiency is low, and its noise resistance needs to be further improved, so it is difficult to realize the online analysis of monitoring signals. For these defaults, the DPCA method, which is a demodulation method based on TFA and PCA, was proposed by Song et al. [27, 28]. Based on this method, the dimension of time-frequency distribution matrix can be reduced to realize the fast demodulation of signals. The computational efficiency of this algorithm is sufficient to realize the online analysis of monitoring signals.

2. Modulation models of acoustic vibration signal

Considering the working characteristics of rotating machinery, during the operation process, due to rotor imbalance, misalignment, flow field instability, and other factors, periodic impact will occur, resulting in significant modulation signal components in the radiated noise of fan equipment. Therefore, according to different working conditions of rotating machinery, its modulation model can be divided into amplitude modulation (AM) signal model under steady-state conditions and amplitude modulation-frequency modulation (AM-FM) signal model under unsteady state conditions. The two working conditions are respectively for constant speed operation and variable speed operation. In this section, typical modulation models of above modulation signals will be illustrated and analyzed, respectively.

2.1 Modulation model of AM signal

Under the condition of constant speed operation, the radiated noise signal produced by rotating machinery contains obvious amplitude modulation signal, which is mainly due to its periodic excitation force. Under steady-state conditions, because the running speed of the rotating machinery remains unchanged, the action cycle of impact force remains unchanged, and finally the characteristic modulation frequency of amplitude modulation signal remains stable.

$$x_{MA}(\mathrm{t}) = A_m \cos(2\pi f_m \mathrm{t}) \sum_{i}^{N} \cos\left(2\pi f_{c,i} \mathrm{t}\right) \tag{1}$$

where x_{MA} is the AM signal of rotating machinery; A_m is the amplitude of the AM signal; f_m is the characteristic frequency of the AM signal; $f_{c,i}$ is the frequency of the carrier signal; N is the total number of carrier signals.

When the spectrum of the carrier signal is line spectrum, its envelope signal has significant periodicity, and its carrier modulated AM signal has obvious spectral characteristics, and the sideband has obvious symmetry, as shown in **Figure 1**. Such features can accurately reflect the characteristic frequency information of the modulated signal. Therefore, for a simple single component AM modulation signal, envelope demodulation, resonance demodulation, spectral kurtosis analysis, and other algorithms can be used to extract the characteristic frequency information of the modulation signal in the monitoring signal.

When the carrier signal spectrum is broadband signal, the envelope signal and spectrum of broadband carrier AM simulation signal are shown in **Figure 2**. The time-domain and frequency domain spectrum characteristics of the amplitude modulation signal are different from those of the single component line spectrum carrier modulation signal.

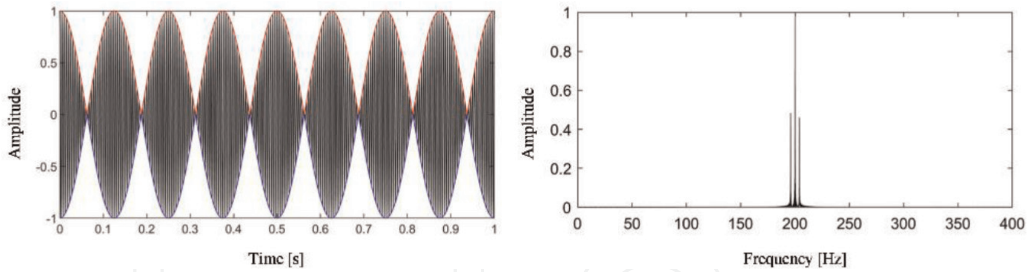

Figure 1.
Mono-component AM signal and its spectrum [29].

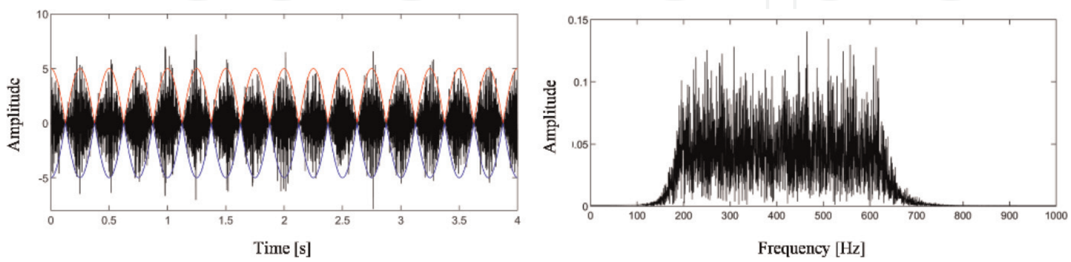

Figure 2.
Wideband carrier AM signal and its spectrum [29].

In time-domain, the envelope signal of wideband carrier modulation signal has deviation, but the overall trend corresponds to the modulation signal, so it can reflect the characteristic modulation information of amplitude modulation signal. In the frequency domain, the spectrum characteristics of wideband carrier modulation simulation signal appear as wideband frequency domain signal. At this time, there is no significant distribution feature in the spectrum of the amplitude modulated signal, so the signal can be demodulated by using the envelope spectrum analysis method, but the characteristic frequency information of the modulated signal cannot be observed directly from its spectrum.

2.2 Modulation model of the AM-FM signal

Under the condition of variable speed operation, the amplitude and frequency of the radiated noise signal generated by rotating machinery are modulated at the same time. At this time, the modulation signal is mainly amplitude modulation frequency modulation signal. The main reason for this signal is the periodic change of the impact force of the rotating machinery with time in the process of variable speed operation. The AM-FM signal of the radiated noise signal of the rotating machinery established in this paper is as follows:

$$x_{MAf}(\mathrm{t}) = A_{mf} \cos\left(\theta_{mf}(\mathrm{t})\right) \sum_{i}^{n} \cos\left(2\pi f_{i} \mathrm{t}\right) \tag{2}$$

where x_{MAf} (t) is the AM-FM signal; A_{mf} is the amplitude of the AM-FM signal; θ_{mf} (t) is the change of the modulated signal angle; f_{mf} (t) is the instantaneous frequency of the AM-FM signal, as expressed in Eq. (3).

$$f_{mf}(\mathrm{t}) = \frac{d\theta_{mf}(\mathrm{t})}{dt} \tag{3}$$

For a typical AM-FM signal, the envelope signal of its timing signal is different from that of a typical AM signal, and its envelope signal does not have typical periodicity. When the carrier signal is a line spectrum carrier signal, the timing waveform of the single component AM-FM signal and its corresponding spectrum distribution are shown in **Figure 3**.

According to the waveform of single component AM-FM signal, at this time, the envelope signal can still reflect the waveform characteristics of the modulation signal, but because the frequency of the modulation signal changes, its waveform does not have periodicity. Different from the spectrum of single component am line spectrum carrier modulation signal, the spectrum of single component AM-FM signal does not have obvious sideband effect and presents a certain bandwidth as a whole, so the corresponding modulation information cannot be obtained according to its spectral characteristics.

When the carrier signal is broadband noise, the time-domain waveform and spectrum distribution of the AM-FM simulation signal of the broadband carrier signal are shown in **Figure 4**. The waveform characteristics of its envelope signal are similar to the envelope signal of single component AM-FM line spectrum carrier modulation signal, which can reflect the waveform of the modulation signal, but there is a certain error. The spectrum of the wideband carrier modulated signal as a whole is a wideband frequency domain signal, which corresponds to the wideband spectrum of the carrier signal as a whole, but it does not reflect the change of the characteristic frequency of the modulated signal. Therefore, it is difficult to extract the characteristics of AM-FM signals using conventional envelope demodulation algorithm.

For the feature extraction of AM-FM signal, the signal resampling technology and demodulation technology are often used. The resampling operation of the monitoring signal of rotating machinery requires the monitoring of phase information. The resampling signal of rotating machinery can be obtained by using the phase information of rotating machinery for data difference and combining the timing signal of the

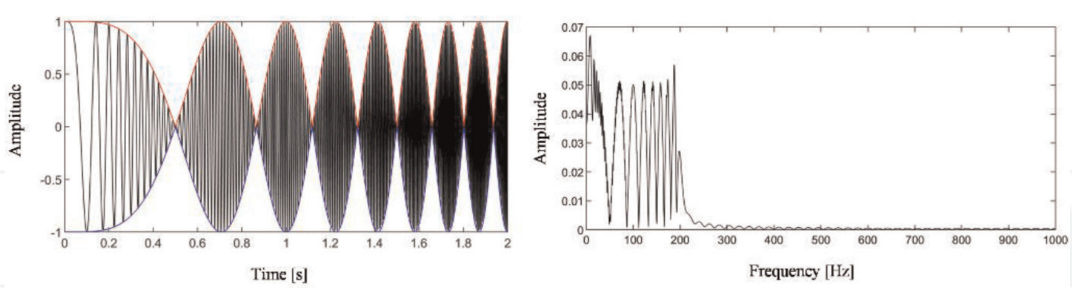

Figure 3.
Mono-component AM-FM signal and its spectrum [29].

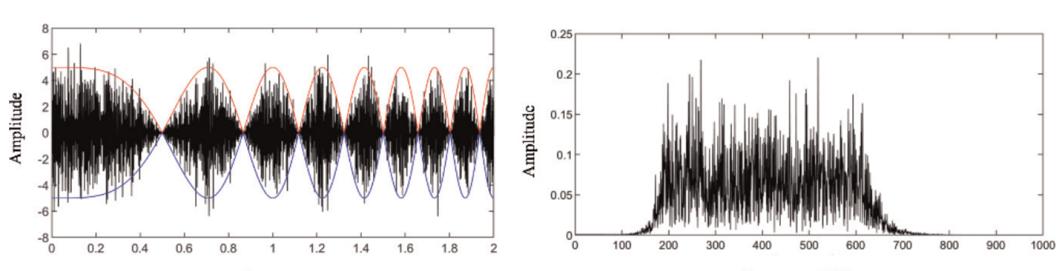

Figure 4.
Wideband carrier AM-FM signal and its spectrum [29].

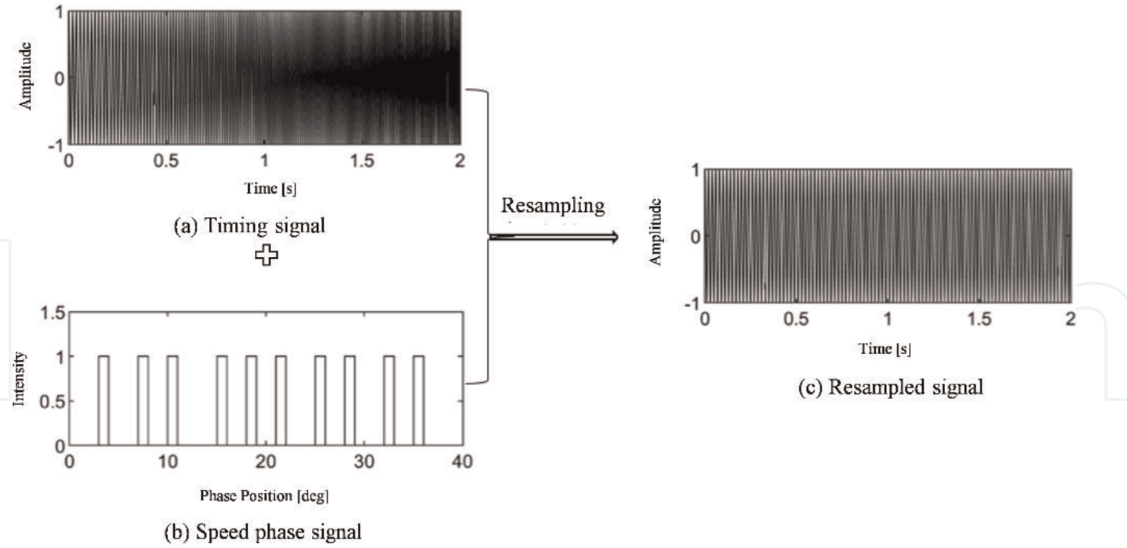

Figure 5.
Monitoring signal resampling [29]. (a) Timing signal; (b) speed phase signal; and (c) resampled signal.

monitoring signal, as shown in **Figure 5**. According to the resampled signal obtained by resampling the phase data of rotating machinery and the radiated noise signal, combined with the method of spectrum analysis, the order modulation information of the acoustic signal of rotating machinery can be obtained.

3. Noise reduction technology and feature extraction method of online fan monitoring signal

3.1 Radiated noise signal components

The acoustic signal of rotating equipment mainly includes three components: deterministic signal, modulated signal, and noise signal [29]. Therefore, the sound radiation model of rotating machinery can be expressed as **Figure 6**. The vibration transmission system of rotating machinery can be regarded as a liner time invariant system. The monitoring signal is the convolution of above three signal components and transmission path function, as illustrated in Eq. (4)

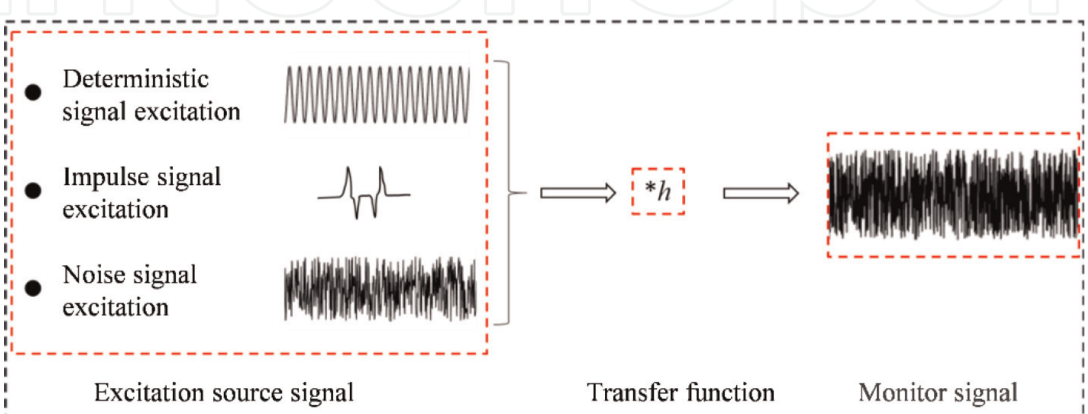

Figure 6.
Acoustic signal model of rotating machinery [29].

$$x(\mathrm{t}) = [x_d(\mathrm{t}) + x_m(\mathrm{t}) + x_e(\mathrm{t})] * h \tag{4}$$

where $x(\mathrm{t})$ is monitoring signal; $x_d(\mathrm{t})$ is deterministic signal component; $x_m(\mathrm{t})$ is modulation signal component; $x_e(\mathrm{t})$ is noise signal component; * represents convolution operation; h is the transfer function from the vibration source to the monitoring point. It is worth noting that the impact of transfer function can be ignored since the transfer function only has a small influence on the frequency characteristics of signal.

The deterministic signal components in the monitoring signal are caused by mechanical faults in the process of mechanical operation, such as rotor imbalance, bolt looseness, and so on. The deterministic signal components can be accurately characterized by functional models, which have first-order statistical characteristics under steady-state conditions as shown in Eq. (5).

$$x_d(\mathrm{t}) = E[x_d(\mathrm{t} + T_d)] \tag{5}$$

where, E [] represents the statistical average function of the signal; T_d represents the period of the signal.

Under steady-state condition, the deterministic signal component is the basis of signal preprocessing analysis since the characteristic frequency and amplitude of the component do not change considerably.

Modulation signal component is the characteristic component in the monitoring signal. The modulation signal component is caused by the periodic impulse of rotating parts in the process of rotation. Under constant speed operation, the modulation signal is AM signal, whose second-order statistical characteristics have significant periodicity as shown in Eq. (6).

$$x_{cr}(\mathrm{t}, \tau) = E[x_m(\mathrm{t})[x_m(\mathrm{t} + \tau)]] \tag{6}$$

where $x_{cr}(\mathrm{t}, \tau)$ is the autocorrelation function of the rotating machinery monitoring signal; τ is the delay time.

Under variable speed operation, the modulation signal is AM-FM signal; the relationship between the order of monitoring signal and the frequency modulation can also be obtained by resampling. In rotating equipment, the fault features are hidden in the modulation signal. Faults of various positions, components, and degrees exhibit distinct characteristics in modulated signals. There is a correlation between fault features and modulation features. Thus, the fault early warning and fault location could be realized. Therefore, the modulation signal components in radiation noise generated by rotating machinery have periodicity of high-order statistics. It is an effective means for the application of rotating machinery condition monitoring, fault early warning, and fault location.

Rotating machinery noise signal components are mainly Gaussian white noise, which does not have the periodicity of first-order, second-order, and higher-order statistics. Therefore, in order to accurately extract the low-frequency acoustic texture feature information of rotating machinery, it is necessary to eliminate noise signal component by utilizing its statistical characteristics.

3.2 Signal preprocessing method

Under the condition of low SNR, the interference of environmental noise and equipment noise leads to serious clutter interference in the radiated noise signal, which is not conducive to the identification and extraction of deterministic characteristic frequencies. The radiation noise is composed of equipment noise and environmental noise. The equipment noise is the noise generated by equipment operation, which refers to the noise with a certain modulated signal component. The environmental noise is the background noise, which refers to noise unrelated to the operation of equipment. The equipment noise contains deterministic signal component and the modulation signal component, while the environmental noise contains noise signal. Signal preprocessing method is an effective noise reduction method for monitoring signals. The preprocessing methods for rotating machinery monitoring signals mainly include time-domain synchronous averaging (TSA) method and auto-regression (AR) model.

3.2.1 Time-domain synchronous averaging

Because the modulated signal components and noise signal components do not have first-order steady-state statistical characteristics, while the deterministic signal components have stable first-order statistical characteristics, synchronous averaging is a commonly used deterministic component extraction and noise reduction method for rotating machinery equipment running at a constant speed, as shown in Eq. (7). TSA is the most commonly used synchronous averaging technology.

$$x_{TSA}(\mathrm{t}) = \lim_{M\to\infty} \frac{1}{2M+1} \sum_{m=-M}^{M} x(\mathrm{t} + mT_{TSA}) \tag{7}$$

where $x(\mathrm{t})$ is the monitoring signal; $2M + 1$ is the number of averaging; T_{TSA} is the duration of averaging period; $x_{\mathrm{TSA}}(\mathrm{t})$ is the TSA signal.

However, under the variable speed operation, the TSA cannot be directly used. The monitoring signal needs to be resampled by the phase signal monitored by the rotating machinery. According to the resampled signal, combined with the angle-domain average processing, the angle-domain averaging signal can be obtained, as shown in Eq. (8).

$$x_{TSA}(\theta) = \lim_{M\to\infty} \frac{1}{2M+1} \sum_{m=-M}^{M} x(\theta + m\theta_{TSA}) \tag{8}$$

where $x(\theta)$ is the resampling monitoring signal; θ_{TSA} is the angle averaging period; $x_{\mathrm{TSA}}(\theta)$ is the angle-domain averaging signal.

However, there are a series of problems in the practical application of TSA. In practice, the feature extraction of deterministic signal components needs to have certain requirements for the resolution of time-domain signals. Moreover, in order to meet the requirements of signal analysis frequency resolution, TSA has higher requirements for the temporal length of monitoring signals and the operating conditions of rotating machinery, which play a certain role in limiting the application of the TSA technology.

3.2.2 Linear prediction based on auto-regression model

Linear prediction is an effective algorithm for extracting the deterministic components in signals. This algorithm can use historical data to achieve accurate prediction of data and then realize the prediction and separation of deterministic components in rotating machinery monitoring signals. The AR model used to extract the deterministic components can be expressed by Eq. (9).

$$x_{AR} = -\sum_{i=1}^{p} q(i)x(n-i) \tag{9}$$

where x_{AR} is the deterministic signal component obtained by linear prediction of monitoring signal; p is the order of AR model; $q(i)$ is weight coefficient. $q(i)$ can be solved by Yule-Walker equations. The process is as follows:

$$\begin{bmatrix} r_{xx}(0) & r_{xx}(-1) & \cdots & r_{xx}(-p+1) \\ r_{xx}(1) & r_{xx}(0) & \dots & r_{xx}(-p-2) \\ \vdots & \vdots & \ddots & \vdots \\ r_{xx}(p-1) & r_{xx}(p-2) & \dots & r_{xx}(0) \end{bmatrix} \begin{bmatrix} q(1) \\ q(2) \\ \vdots \\ q(p) \end{bmatrix} = - \begin{bmatrix} r_{xx}(1) \\ r_{xx}(2) \\ \vdots \\ r_{xx}(p) \end{bmatrix} \tag{10}$$

The residual signal refers to an interference signal, which is composed of modulation signal and noise signal. The residual signal was obtained by the residual between monitor signal and linear prediction signal, as shown in Eq. (9) and Eq. (11). In addition, by using the residual between the original monitoring signal and the linear prediction signal, the residual signal composed of the modulated signal and the noise signal can be effectively obtained, as shown in Eq. (11).

$$x_m(\mathrm{t}) + x_e(\mathrm{t}) = x(\mathrm{t}) + \sum_{k=1}^{p} a(k)x(\mathrm{t}-k) \tag{11}$$

where $x(\mathrm{t})$ is monitor signal; $x_{\mathrm{m}}(\mathrm{t})$ is the modulated signal; $x_{\mathrm{e}}(\mathrm{t})$ is the noise signal; $a(k)$ is the weight coefficient of linear prediction. $a(k)$ can be obtained by linear transformation of AR function of monitoring signal. The process is as follows:

$$r_{xx}(i) = \frac{1}{N}\sum_{n=0}^{N-1} x(n)x(n-1), 0 \le i \le p-1 \tag{12}$$

Therefore, through the linear prediction, the SNR of the modulated signal can be effectively improved, and then, the interference component in the modulated signal can be reduced.

In order to better compare the preprocessing performance of the two algorithms, Gaussian white noise with an SNR of −15 dB is added to the signal model for analysis and verification, as shown in **Figure 7**. The raw signal, TSA signal, AR signal, and their spectrum are shown in **Figure 7**, respectively.

When SNR = −15 dB, the raw signal contains a lot of noise, and the SNR is very low. The spectrum of the raw signal has completely lost the ability to characterize the deterministic signal components. When TSA is used as the preprocessing analysis method, the spectrum of the preprocessed signal contains a certain characteristic frequency within the frequency range of 0–100 Hz, but the spectrum still contains a lot of interference frequencies. At this time, using TSA as the preprocessing method has lost its effect.

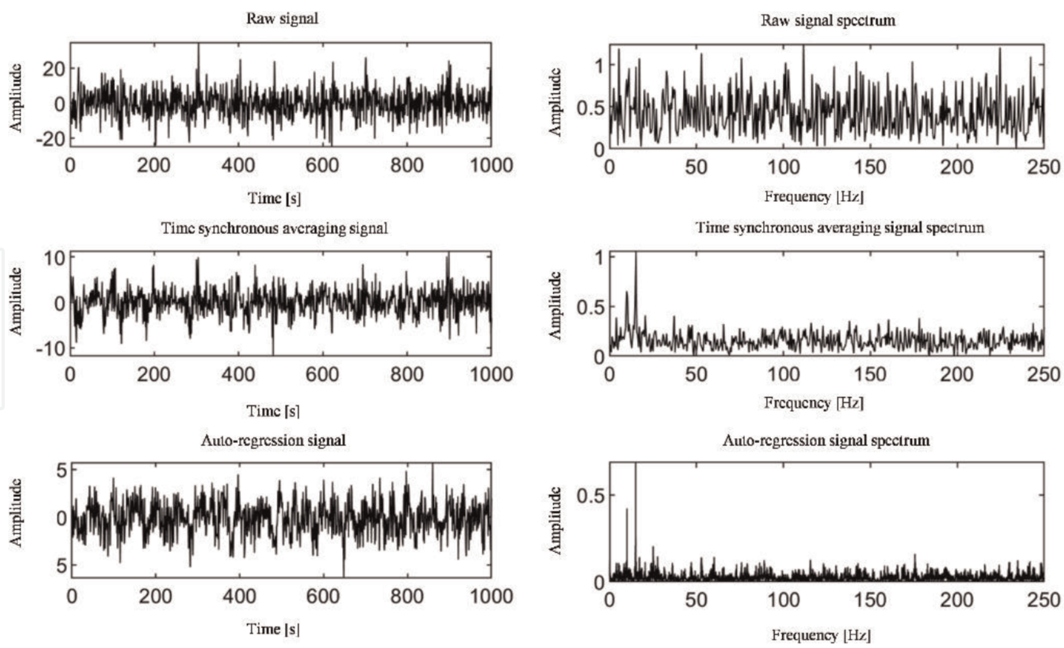

Figure 7.
Comparison of noise reduction. (SNR = −15 dB) [29].

When the linear prediction preprocessing method is adopted, the noise can be effectively reduced according to the waveform of its time-series signal, and the analysis results can be obtained based on the linear prediction as the preprocessing method. There is a low degree of interference in the spectrum, and the characteristic frequency of deterministic signal components can be more accurately located. Therefore, under the condition of low SNR, the preprocessing algorithm based on linear prediction is better than the time-domain average algorithm. In the later sections of this chapter, the preprocessing method based on the AR model was adopted by default.

4. Cases of multi-type typical fault identification fan equipment based on modulation model

4.1 Common failures of multi-type fan equipment

Cyclostationary signal, a kind of widely existing non-periodic and non-stationary signal, is a modulated signal component of rotating machinery. However, the second-order statistical characteristics of cyclostationary signals have certain periodicity, which provides a research basis for cyclic feature extraction of modulated signals. Cyclic feature extraction method is a signal post-processing method based on signal demodulation, which reveals the potential periodicity of the monitoring signal and then obtains more accurate signal modulation information than the traditional signal processing methods. For cyclostationary signals, the enhanced envelope spectrum obtained by Fast-SC [23] could realize cyclic feature extraction. In this section, in order to verify the effectiveness of fault identification and feature extraction methods for different types of fans, experiments of jet fans and axial fans have been carried out. The test rigs of multi-type fan equipment are shown in **Figure 8**. Based on the vibration acceleration signals collected in their experiments, the enhanced envelope spectrum (EES) is calculated, and the characteristic frequency of the fault is extracted.

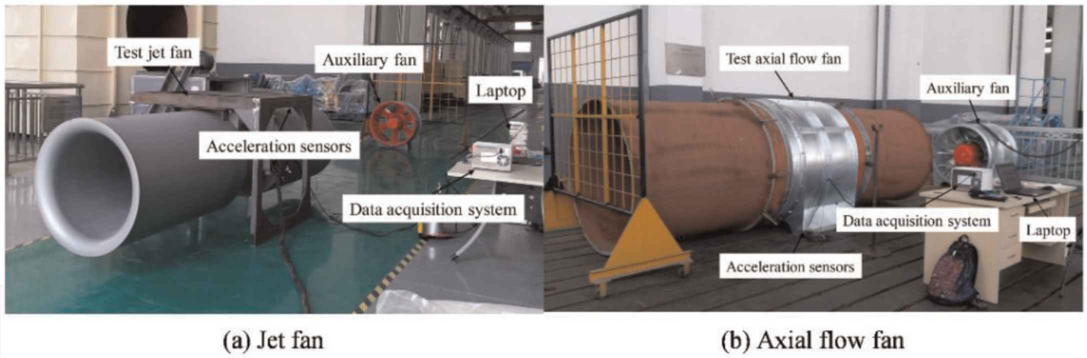

Figure 8.
Test rigs of a multi-type fan [1]. (a) Jet fan and (b) axial flow fan.

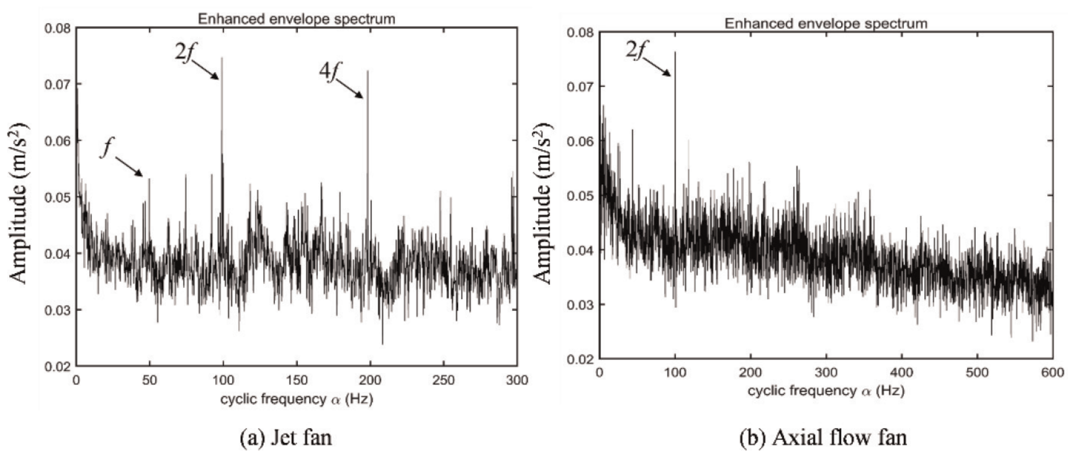

Figure 9.
Enhanced envelop spectrum in normal working conditions [1]. (a) Jet fan and (b) axial flow fan.

For fault diagnosis, fault characteristics can be used as a criterion for detailed fault diagnosis. Different types of fans have different criteria for fault diagnosis:

For a jet fan, the EES of normal working conditions is shown in **Figure 9a**. It shows that the labeled cyclic frequencies $\alpha = f$, $2f$, $4f$ can represent the characteristic frequencies of the jet fan in normal working conditions, in which f is the shaft frequency of a jet fan. For an axial flow fan, the EES of normal working conditions is shown in **Figure 9b**. It shows that the labeled cyclic frequencies $\alpha = 2f$ are the characteristic frequencies of the axial flow fan in normal working conditions, in which f is the shaft frequency of axial flow fan.

In the fault experiments of a jet fan and an axial fan, bolt looseness faults were set up in the two experimental devices, respectively. The EES of the jet fan in bolt looseness fault is shown in **Figure 10a**. It is indicated that in the labeled cycle frequencies, $\alpha = f$, $2f$, $4f$, $5f$,and $6f$ are the characteristic frequencies of bolt looseness fault of the jet fan. The EES of the axial flow fan in bolt looseness fault is shown in **Figure 10b**. It is shown that the labeled cycle frequencies $\alpha = 2f$, $4f$, $6f$ are the characteristic frequencies of bolt looseness fault of the axial flow fan. The comparison shows that the cyclic feature extraction method can effectively diagnose the bolt looseness fault of an axial flow fan and a jet fan. In addition, the cycle frequency of bolt loosening fault of the jet fan and axial fan is different, so the cyclic feature extraction can be extended to the fault diagnosis of the subway ventilation system.

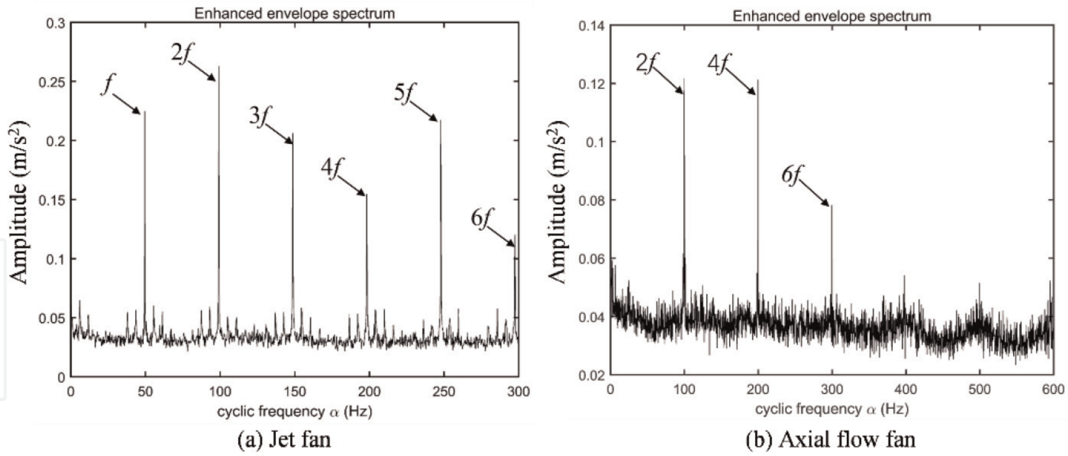

Figure 10.
Enhanced envelop spectrum in bolt looseness fault [1]. (a) Jet fan and (b) axial flow fan.

4.2 Typical faults of the axial flow fan equipment

For different types of typical faults, besides the bolt loosening fault of the axial flow fan device, the EES of blade slight damage fault is also calculated, and the characteristic frequencies of acoustic signals and vibration acceleration signals before and after blades abrasion are extracted, respectively.

For acoustic signals, the EES of normal working conditions is shown in **Figure 11a**. It shows that the labeled cyclic frequencies $\alpha = 2f, 6f, 8f$ can represent the characteristic frequencies of acoustic signals in normal working conditions. The EES of damaged blades condition is shown in **Figure 11b**. It is indicated that in the labeled cycle frequencies, $\alpha = 4f$, $6f$, and $8f$ are the characteristic frequencies of blades abrasion fault of the axial fan.

For vibration acceleration signal, the calculated EES before and after blades abrasion are shown in **Figure 12**. It shows that the labeled cyclic frequencies $\alpha = f, 2f, 4f, 6f, 8f$ can represent the characteristic frequencies of vibration acceleration signals in normal working and blades abrasion conditions. This is because the blades abrasion failure set in the experiment was not destructive damage, so no new characteristic

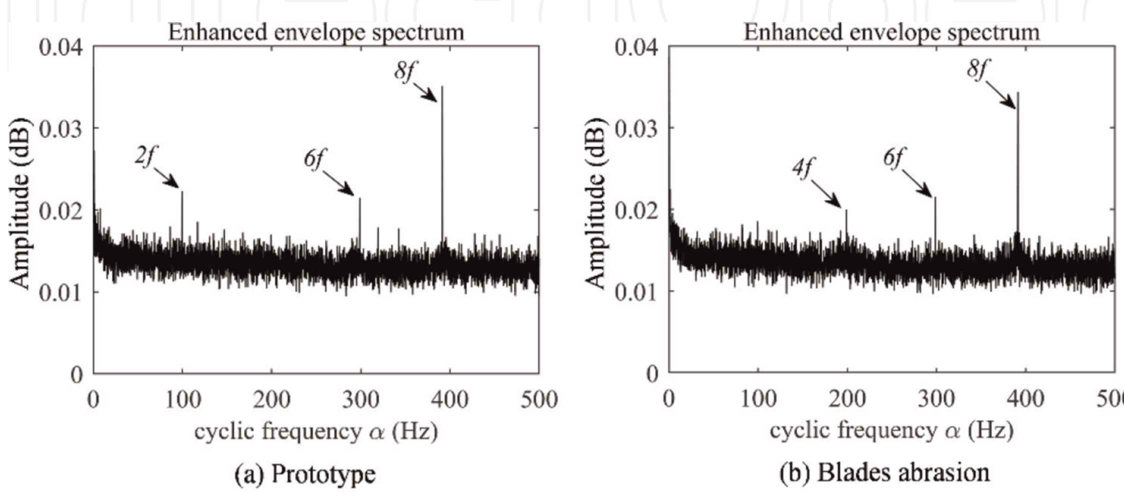

Figure 11.
Enhanced envelop spectrum of acoustic signals. (a) Prototype and (b) blades abrasion.

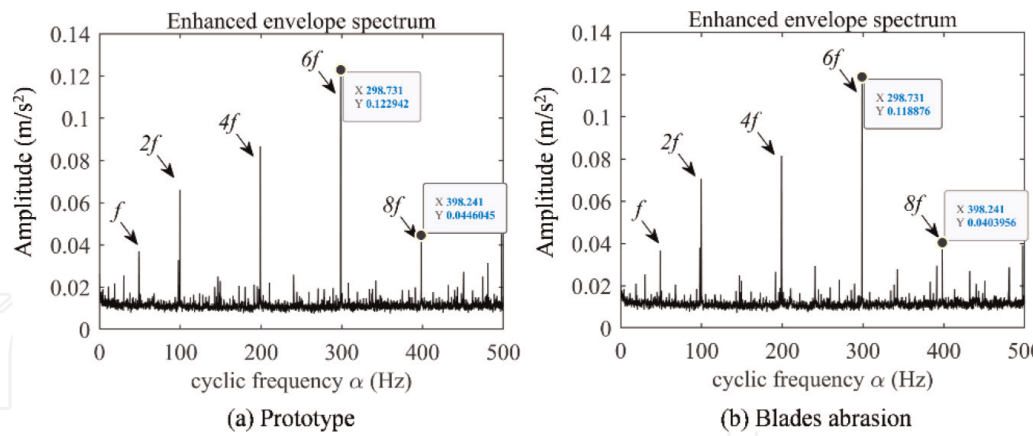

Figure 12.
Enhanced envelop spectrum of vibration acceleration signals. (a) Prototype and (b) blades abrasion.

frequency is generated in the enhanced envelope spectrum under blades abrasion failure. However, compared with normal working conditions, the amplitude of the cyclic frequency caused by blades abrasion fault changes. These amplitude changes can also be used as one of the characteristics of blades abrasion fault, so as to realize the prediction of destructive blades abrasion fault.

5. Conclusion

In this chapter, the key technologies of online monitoring and intelligent diagnosis are discussed. The feature extraction method based on signal demodulation offers a powerful solution to fault identification. In addition, common signal noise reduction methods are researched. Finally, the cases of typical rotating machinery failure were simulated by experiment. The main conclusions are as follows:

1. According to different operational conditions of rotating machinery, its modulation model can be divided into AM signal model and AM-FM signal model. The frequency modulation could be extracted by these models. The establishment of modulation signal model provides the research foundation for a signal demodulation method.

2. Signal preprocessing methods could reduce or eliminate the signal noise, which effectively improves the SNR for further analysis.

3. The fault diagnosis method based on signal demodulation is verified in experiments of bolt looseness and blades abrasion fault. The experimental results show that the amplitudes of cyclic frequency components can reveal the spectral characteristics of the ventilator.

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