Rotor-Mechanical Coupled Fault Feature Extraction Based on Second-order Blind Identification

Feng Miao*, RuZhi Feng and XianLi Wang

1 School of Physical and Electrical Information, Luoyang Normal University, Luoyang, Henan, 471022, China
2 Henan Mechanical and Electrical Vocational College, Zhengzhou, Henan, 451191, China
*miaofeng3699@163.com

Abstract. Noise reduction usually is conducted before analysis of mechanical fault feature, which could damage effective signals. This article proposes an algorithm of blind source separation based on the second-order statistics. The method focuses on noise separation rather than noise removal. So there are no harms to effective signals. This idea might provide a new way for noise reduction. The algorithm of blind source separation based on the second-order statistics blind identification is applied to seismic data. The results show that the algorithm is effective, noises are separated and removed, and the rotor fault feature is picked up.

1. Introduction

The extraction of mechanical failure features in the noise environment has always been a complex problem [1-3]. In the context of unknown noise, it is often difficult to extract effective fault characteristics if the effects of noise are ignored. Therefore, the influence of noise must be taken into account in the mechanical fault diagnosis based on blind separation theory. In the literature [4-9], the vibration signal is de-noised and separated by wavelet transform, wavelet packet, wavelet filtering, autocorrelation and blind separation method, and then the fault signal is extracted from the separated signal. Literature [10] were carried out noise reduction, and carried out simulation and experimental research. In the separation of mechanical fault sources, although the use of noise reduction pretreatment method has achieved some success, there are some shortcomings, first of all, different working conditions noise is different, using different de-noising method will come to different separation results.

In order to solve this problem, this paper applies the blind separation theory to the noise reduction process. The key is to separate the noise rather than eliminate the noise. Therefore, it does not lose the effective signal when separating the noise, and provides a new method for noise processing. In this paper, a self-extraction method based on second order blind identification is proposed. This method introduces the concept of gradient change rate in the original self-extraction algorithm, which effectively reduces the noise. Through the simulation and the actual rotor vibration data processing shows that this algorithm effectively curb the noise, improve the accuracy of sampling data.
2. Signal model

Blind source separation problem refers to the process of recovering individual components only by observing signals without knowing the parameters of the source signal and the transmission channel. The hybrid model is represented as \[ \mathbf{x}(k) = 

\mathbf{H}_{\mathbf{s}}(k) + n(k) \]  \tag{1}

Where \( \mathbf{x}(k) = [x_1(k), x_2(k), \ldots, x_M(k)]^T \) is a M-dimensional random observation vector. In the case of noisy interference, \( \mathbf{H} \) is a mixed matrix of \( M \times N \) with an unknown full rank; \( \mathbf{s}(k) = [s_1(k), s_2(k), \ldots, s_N(k)]^T \) is an N-dimensional source signal, the components of the source signal are assumed to be statistically independent and contain at most one Gaussian noise, otherwise they cannot be separated; \( n(k) = [n_1(k), n_2(k), \ldots, n_M(k)]^T \) is an M-dimensional noise signal.

In this article, unless otherwise stated, the following assumptions are made:

1. The mixed matrix \( \mathbf{A} \in \mathbb{R}^{M \times N} \) full rank;
2. The source signal is irrelevant to the space-time domain, and the time-domain associated zero mean random signal;
3. The source signal changes in variance, is the second order non-stationary, or smooth signal;
4. The source signal and noise are independent, can be airspace color, time domain white, that is \( E(n(k)n^T(k-p)) = \delta_{p0} \mathbf{R}_n(p) \)

Where \( \delta_{p0} \) is the Kronecker delta function; \( \mathbf{R}_n \) is an arbitrary \( M \times N \)-order matrix.

3. Algorithm Based on Second Order Blind Identification

In the above hypothesis, where the observed signal vector \( \mathbf{x}(k) \) is satisfied for the correlation function matrix of nonzero delay \( p \):

\[
\mathbf{R}_s(0) = E\{\mathbf{x}(k)\mathbf{x}^T(k)\} = H\mathbf{R}_{\mathbf{s}}(0)H^T + \mathbf{R}_n(0) \tag{2}
\]

\[
\mathbf{R}_s(p) = E\{\mathbf{x}(k)\mathbf{x}^T(k-p)\} = H\mathbf{R}_{\mathbf{s}}(p)H^T \tag{3}
\]

Where \( \mathbf{R}_s(0) = E\{\mathbf{x}(k)\mathbf{x}^T(k)\} \) and \( \mathbf{R}_s(p) = E\{\mathbf{x}(k)\mathbf{x}^T(k-p)\} \) are nonzero different elements diagonal matrix. When the number of observed signals \( N \) is greater than the number \( M \) of the source signal, when the noise covariance matrix \( \mathbf{R}_n = R_n(0) = E\{\mathbf{x}(k)\mathbf{x}^T(k)\} = \sigma_n^2 \mathbf{I}_m \) special form (When the signal-to-noise ratio is high, the noise variance \( \sigma_n^2 \) is estimated from the mean singular value of \( \mathbf{R}_s(0) \) or the singular value of \( \mathbf{m-n} \mathbf{R}_s(0) \), the unbiased estimation of the covariance matrix of formula (2) is as follows

\[
\tilde{\mathbf{R}}_s(0) = \mathbf{R}_s(0) - \sigma_n^2 \mathbf{I}_m = H\mathbf{R}_{\mathbf{s}}(0)H^T \tag{4}
\]

In order to identify the mixed matrix \( \mathbf{H} \), we can estimate the diagonalization of \( \tilde{\mathbf{R}}_s(p) \) and \( \tilde{\mathbf{R}}_s(0) \) by the covariance matrix of Eq. (3) and (4).

The second-order blind identification algorithm (the number of sensors is greater than the number of source signals) is as follows:

1. Estimate the correlation matrix of the sensor signal

\[
\tilde{\mathbf{R}}_s(0) = \frac{1}{N} \sum_{k=1}^{N} \mathbf{x}(k)\mathbf{x}^T(k) \tag{5}
\]

2. Calculate the SVD or EVD of \( \tilde{\mathbf{R}}_s(0) \), ie

\[
\tilde{\mathbf{R}}_s(0) = \mathbf{U}_s \sum_s \mathbf{V}_s^T = \mathbf{V}_s \mathbf{A}_s \mathbf{V}_s^T = \mathbf{V}_s \mathbf{A}_s \mathbf{V}_s^T + \mathbf{V}_s \mathbf{A}_n \mathbf{V}_n^T \tag{6}
\]
Where $V_s = [v_1, v_2, \cdots, v_n] \in R^{n \times m}$ contains the eigenvectors corresponding to the $n$ main eigenvalues of $\Lambda_s = \text{diag}\{\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_n\}$. Similarly, the matrix $V_N \in R^{m \times (m-n)}$ contains $m-n$ noise eigenvalues $\Lambda_N = \text{diag}\{\lambda_{m+1} \geq \cdots \geq \lambda_m\}$ (where $\lambda_{m+1}, \lambda_{m+2}, \ldots \lambda_m$) corresponds to the noise eigenvector. There are usually typical relationships between eigenvalues $\lambda_1 \geq \lambda_2 \geq \cdots \lambda_m \approx \cdots \approx \lambda_m$ ($m> n$).

(3) Estimate the white noise variance $\sigma^2$ for $m-n$ least significant eigenvalues or singular values. And do pre-whitening processing, such as

$$\bar{x}(k) = \tilde{\Lambda}^{-1/2}_s V^T_s x(k) = Qx(k)$$

Where: $\tilde{\Lambda}_s = \text{diag}\{(\lambda_1 - \sigma^2_1), (\lambda_2 - \sigma^2_2), \ldots, (\lambda_m - \sigma^2_m)\}$.

(4) In the case of delay $p \neq 0$, we estimate the covariance matrix of $\bar{x}(k)$, and carry out SVD, that is,

$$\bar{R}_x(p) = \frac{1}{N} \sum_{k=1}^{N} \bar{x}(k) \bar{x}^T(k-p) = U^T \Sigma V^T$$

(5) whether there is a difference in the singular value corresponding to the diagonal matrix $\Sigma$ of the delay $p$. If there is no significant difference, select a different delay $p$ and return to step (3). If there is a significant difference between the singular values and the distance is far from each other, then the estimated mixing matrix is

$$\tilde{H} = Q^T U = V_s \tilde{\Lambda}^{1/2}_s U = U^T \Sigma V^T x(k)$$

It is estimated that the source signal with noise is

$$y(k) = \tilde{s}(k) = U^T \bar{x}(k) = U^T \tilde{\Lambda}^{1/2}_s V^T_s x(k)$$

4. Simulation research and analysis

4.1. Evaluation Criteria
In order to evaluate the effect of signal separation effectively, the similarity coefficient is used as the evaluation index of the difference between the separation signal and the source signal. The similarity coefficient is defined as:

$$\xi_{ij} = \xi(y_i, s_j) = \frac{1}{\sqrt{\sum_{i=1}^{M} y_i^2(t) \sum_{j=1}^{M} s_j^2(t)}} \left| \sum_{i=1}^{M} y_i(t) s_j(t) \right|$$

In the formula, when, is constant, , that is, the separation of the signal amplitude difference; when the separation signal and the source signal is independent of each other . It is also said that if the similarity coefficient matrix is equal to 1 for each row and each column and only one element is close to zero, then the separation effect of the algorithm is considered to be ideal.

4.2. Simulation
In order to validate the method proposed in this paper, we first simulate the simulation. According to the known vibration signal model of the rotating machinery, the simulation source is constructed as follows:

$$s_1(t) = \sin(0.5t)$$
$$s_2(t) = \sin(0.3t) \cos(10t) + \sin(2t)$$
$$s_3(t) = 4\text{rand}$$

Sampling frequency 1000Hz, sampling length of 256 points, aliasing matrix $H$;
Generating a mixed signal $H$ shown in Figure 2

$$H = \begin{bmatrix} 0.965 & 0.334 & 0.718 \\ 0.666 & 0.523 & 0.778 \\ 0.726 & 0.273 & 0.081 \end{bmatrix}$$

Fig. 1 The simulative signal

Fig. 2 The mixture of simulative signal

Fig. 3 The separated signal using second-order statistics blind identification

| Signal vector | Similarity coefficient $\xi_1$ | Similarity coefficient $\xi_2$ | Similarity coefficient $\xi_3$ |
|---------------|-----------------|-----------------|-----------------|
| $y_1$         | 1.00000         | 0.00011         | 0.00023         |
| $y_2$         | 0.02132         | 1.00000         | 0.00693         |
| $y_3$         | 0.01321         | 0.07685         | 1.00000         |

From the mixed signal in Figure 2, it is difficult to distinguish the characteristics of the observed signal. As can be seen from Figure 3, the separated signal and the source signal are basically the same, only the amplitude is inconsistent, it is because the blind signal separation Amplitude and order of the inconsistency; at the same time random noise signal is a good separation. As can be seen from Table 1, the maximum value of the similarity coefficient between the separation signal and the source signal is 1, the similarity is close to 100%, and the separation effect is achieved.

5. Experiment

In order to verify the application of the second-order blind identification in the double-rotor mechanical fault signal separation, this paper uses the algorithm to analyze the real double-rotor fault vibration signal. The experimental sampling frequency is 5000Hz, the sampling point is 5120, the speed is 2800r/min. Three-way sensor installation location shown in Figure 4. When the rotor rubbing fault and imbalance fault exist at the same time, the three sensor signals were shown in Figure 5; through the second-order blind identification after separation of the time domain signal shown in Figure 7. It is difficult to determine the specific fault of the rotor from the time-domain waveform of the observation signal and the separated signal. For the comparison of the complex vibration characteristics of the two-span rotor before and after the separation, the data signal is analyzed before...
and after the separation, and the spectrum of the observed signal. Figure 8 shows the spectrum of the isolated signal.

It can be seen from Figure 6, the vibration signal is completely covered by the noise, and the fault features of the rotor cannot be reflected. As can be seen from the first picture in fig.8, the tributes of 50Hertz are highlighted and the signals of other frequencies are contained; in the two figure in addition to the fundamental frequency spectrum peak obviously, \(2 \times\), \(3 \times\) also have a small peak exists, the performance of the imbalance of the frequency characteristics; the fifth figure shows that the signal in the time domain and frequency domain showed randomness, can be judged as noise signal.

6. Conclusion

In the case of mechanical fault feature extraction based on blind separation theory, the influence of noise has always been an unsolved problem. Due to the complexity of the mechanical conditions, it is difficult to separate the mechanical failure. In this paper, the blind separation theory is applied to de-
noising, the key is to separate the noise rather than eliminate the noise, so the noise is not lost when the effective signal for noise processing provides a new method. The simulation results show that the algorithm is a good way to separate the random noise and achieve a good separation result. Finally, the proposed method is applied to the fault feature extraction of the double-span rotor. The experimental results also verify the validity of the proposed method. The study of this paper provides an effective method for rotor fault feature extraction in noise environment.

Acknowledgments
The research described in this paper was supported by Foundation of He'nan Educational Committee (16A470021) and key scientific and technological project of Henan Province (172102210097).

References
[1] Z. Peng, Y. He, F. Chu, Vibration signal analysis and feature extraction based on reassigned wavelet scalogram, Journal of Sound and Vibration 253 (5) (2002) 1087-1100.
[2] Z.N. Li, Q.Q. Ding, Z.T. Wu, C.J. Feng, G.B. Yang, Blind system identification and fault diagnosis, Journal of Zhejiang University (Engineering Science) 37 (2) (2003) 215-220.
[3] Miao Feng, Zhao Rongzhen. Separating for nonlinear mixed rotor fault signals with violent pulse interferences. Journal of Vibration, Measurement& Diagnosis,(2014)34(4):625-630.
[4] Lei Yanbin, Li Shunming, Men Xiuhua, et al. Separating mixed rotor vibration signals based on auto-correlation de-nosing[J]. Journal of Vibration and Shock.(2011)30(1):218-222.
[5] Li Zhinong, Liu Weibing, Yi Xiaobing. Underdetermined blind source separation method of machine faults based on local mean decomposition. Journal of Mechanical Engineering, 2011, 47(7): 97-102.
[6] Wang Jian guo, Li Jian, Wan Xudong. Fault feature extraction method of rolling bearings based on singular value decomposition and local mean decomposition [J]. Journal of Mechanical Engineering, 2015, 51(3): 104-110
[7] Antoni J. Blind separation of vibration components: Principles and demonstrations[J]. Mechanical Systems and Signal Processing, 2005,19(6): 1166-1180.
[8] A.Ghazdali,M.ElRhabi,H.Fenniri. Blind noisy mixture separation for independent/dependent sources through a regularized criterion on copulas, Signal Processing,131 (2017) 502-513.
[9] Theodor D. Popescu. Blind separation of vibration signals and source change detection-Application to machine monitoring. Applied Mathematical Modelling 34 (2016) 3408-3421.
[10] A Ypma, A Leshem. Blind Separation of Machine Vibration with Bilinear Forms. in Proceeding of ICA-2000, Helsinki, June, 2000, 405-410.