Int J Adv Manuf Technol (2006) 28: 855–862
DOI 10.1007/s00170-004-2353-7

ORIGINAL ARTICLE

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Application of the blind source separation method to feature extraction of machine sound signals

Received: 24 April 2004 / Accepted: 20 July 2004 / Published online: 15 March 2006

Abstract As the result of vibration emission in air, a machine sound signal carries important information about the working condition of machinery. But in practice, the sound signal is typically received with a very low signal-to-noise ratio. To obtain features of the original sound signal, uncorrelated sound signals must be removed and the wavelet coefficients related to fault condition must be retrieved. In this paper, the blind source separation technique is used to recover the wavelet coefficients of a monitored source from complex observed signals. Since in the proposed blind source separation (BSS) algorithms it is generally assumed that the number of sources is known, the Gerschgorin disk estimator method is introduced to determine the number of sound sources before applying the BSS method. This method can estimate the number of sound sources under non-Gaussian and non-white noise conditions. Then, the partial singular value analysis method is used to select these significant observations for BSS analysis. This method ensures that signals are separated with the smallest distortion. Afterwards, the time-frequency separation algorithm, converted to a suitable BSS algorithm for the separation of a non-stationary signal, is introduced. The transfer channel between observations and sources and the wavelet coefficients of the source signals can be blindly identified via this algorithm. The reconstructed wavelet coefficients can be used for diagnosis. Finally, the separation results obtained from the observed signals recorded in a semi-anechoic chamber demonstrate the effectiveness of the presented methods.

Keywords Blind source separation · Feature extraction · Gerschgorin disk estimator · Machine sound · Mechanical fault diagnosis · Partial singular value decomposition · Time-frequency separation algorithm

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1 Introduction

Most fault diagnosis technologies are based on vibration signal analysis. However, while it is difficult to detect vibration signal and it is ineffective to make fault diagnosis based on vibration signal analysis, the machine sound signal is observed and the sound features can be obtained to make fault diagnosis. This is an acoustic based diagnosis (ABD) technique [1]. The ABD method possesses many advantages, such as provide easy measurement and having no effect on the working condition of machine. The fundamental problems for ABD technique is that the sound signal has very low signal-to-noise ratio (SNR) and it is not effective in obtaining sound features via traditional Fourier analysis [2]. In the acoustic field, the interference of other sound sources is often strong and sometimes it is even stronger than the monitored source itself. The sound signal of the monitored source is usually immersed in the complex observed signal. Thus, to obtain the useful information regarding the monitored system, an effective method for removal of interference and feature extraction must be designed.

In [3], blind source separation (BSS) is used to remove the spectral interference of uncorrelated sources and to recover the spectra of sources. Though the spectrum of the monitored source can be recovered via this method, the fast Fourier transform (FFT) analysis is proved to have little effect in sound feature extraction. In [2] and [4], the wavelet transform is shown to be an effective method for sound feature extraction. In reconstructing the wavelet coefficients, the sound features are obtained as a purified sound signal or a symmetrised dot pattern. But the validity of this method is reduced while there exists a strong interference of uncorrelated sources. In this paper, the above techniques are combined. The blind source separation method is used to remove the interference of uncorrelated sources and to recover wavelet coefficients of the sources. Then, using the aforementioned reconstructing techniques for recovered wavelet coefficients, the specific features of sources can be obtained for diagnosis. Since each source is recovered by the BSS method, this approach is even suitable to multi-systems condition monitoring and fault diagnosis.

In previous BSS algorithms, the number of sources is typically assumed to be known [5–10]. In practice, however, the number of sound sources is usually unknown at first. So this paper proposes the modified Gerschgorin disk estimator method for determining the number of sound sources [11]. For the purpose of estimating the number of sources, the number of observed signals is chosen to be as great as possible, since it must be larger than the number of sources. But for BSS analysis, only the same number of observations as the number of sources is required, theoretically. In previous BSS algorithms, all observations are used and those that are significant for BSS analysis are not considered. Thus, the partial singular value analysis technique is developed in this paper [12]. This method is applied to selecting the most significant signals among all observed signals for BSS analysis. Then, the BSS algorithm suitable to recovery of wavelet coefficients of source signals is investigated. The time-frequency separation algorithm, an effective algorithm for the blind separation of non-stationary signals, is used to identify the transfer channel between the sources and the observations [8]. While the transfer channel is blindly identified, the wavelet coefficients of each source signal can be recovered via the traditional source-identification technique. Finally, the experiments are conducted in semi-anechoic chamber and experimental results demonstrate the effectiveness of the proposed methods.

This paper is organized as follows: in Sect. 2, the problem model and blind source separation technique are discussed; in Sect. 3, the modified Gerschgorin disk estimator method is employed to estimate the number of sound sources, and then the partial singular value analysis method is developed to select significant observations for BSS analysis; in Sect. 4, the time-frequency separation algorithm is introduced to identify the transfer channel and to recover the wavelet coefficients of sources; in Sect. 5, the experimental results and analysis are given; finally, Sect. 6 offers our conclusions.

2 Problem model and blind source separation

Suppose there exist M sound sources, which may come from one or more machines. The source signals $s_j(t)(j = 1, \dots, M)$ are assumed to be mutually independent and additive. The microphones are arranged to record the sound signals. To achieve source separation, the number of microphones N must satisfy the condition of $N \geq M$ [5, 6]. Generally, the observed signals $x_i(t)(i = 1, \dots, N)$ are the contribution of all source signals. In an acoustic-based monitoring process, the transfer channel between observations and sources may be considered to mix instantaneously [13]. Thus, the observed signals are written as:

$$x_i(t) = \sum_{j=1}^{M} \left[a_{ij} s_j(t)\right] + n_i(t) \text{ for } i = 1, L, N \tag{1}$$

where a_{ij} is an unknown mixing coefficient between the jth source and the ith measuring position. The observed signals $x_i(t)$ $(i = 1, \dots, N)$, the source signals $s_j(t)(j = 1, \dots, M)$ and the mixing coefficients $a_{ij}(i = 1, \dots, N; j = 1, \dots, M)$ are expressed in vector or matrix form, and there are $\boldsymbol{X}(t) = (x_1(t), x_2(t), \cdots, x_N(t))^T$, and $\boldsymbol{A} = (a_{ij})_{N \times M}$. Eq. 1 is rewritten in matrix form as:

$$\boldsymbol{X}(t) = \boldsymbol{A}\boldsymbol{S}(t) \tag{2}$$

where matrix $\boldsymbol{A}$ is referred to as the "mixing matrix".

Blind source separation was originally introduced by Jutten and Herault [5]. It is a fundamental technique for signal processing and data analysis that allows for the recovery of unknown source signals from observed signals under the condition of unknown transfer channel. The only prior information utilized for BSS is the mutual independence of sources and the linearity of transfer channel [5–10]. Thus, the BSS technique is especially suitable to resolve the problem of machine sound separation, for which it is very difficult for machine sound propagation to establish the model of transfer channel between sources and observations.

The problem of BSS includes the reconstruction of independent source signals from observations. The general process of BSS is shown in Fig. 1. Under the restriction of a contrast function that serves as an objective function that weighs the independence of signals, and the unknown mixing matrix $\boldsymbol{A}$ or separating matrix $\boldsymbol{B}$, that is the Moore-Penrose pseudo-inverse of mixing matrix, is estimated. Then the sources are recovered as:

$$\hat{\boldsymbol{S}}(t) = \hat{\boldsymbol{B}}\boldsymbol{X}(t) \tag{3}$$

Matrix $\boldsymbol{B}$ or $\boldsymbol{A}$ can be estimated via "closed-form" algorithms or "data-iterative" algorithms [9]. "Closed-form" algorithms collect some statistics of $\boldsymbol{X}(t)$ in a single pass, and then use these statistics to estimate the mixing matrix $\boldsymbol{A}$. "Data-iterative" algorithms attempt to find the separating matrix $\boldsymbol{B}$, such that some empirical statistics of the reconstruction $\hat{\boldsymbol{S}}(t)$ minimize the contrast function.

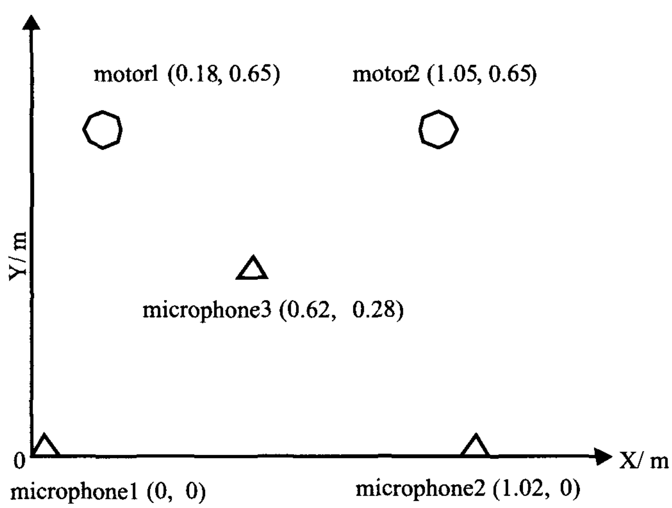

Fig. 1. Position map of sources and microphones

The problem of blind source separation has two inherent ambiguities [9, 10]: first, it is not possible to know the original labeling of the sources; hence, any permutation of the estimated sources is also a satisfactory solution. The second ambiguity is that it is inherently impossible to uniquely identify the source signals. This is because the exchange of a fixed scalar factor between a source signal and the corresponding column of the mixing matrix $\boldsymbol{A}$ which does not affect the observations, as is shown by:

$$X(t) = AS(t) = \sum_{i=1}^{N} \left[\frac{a_i}{c_i} (c_i s_i(t)) \right] \tag{4}$$

where c_i is an arbitrary factor, and $\boldsymbol{a}_i$ denotes the ith column of $\boldsymbol{A}$.

For feature extraction, it is shown that any permutation of the estimated sources only changes the labeling of source in vector $\boldsymbol{S}(t)$. The feature extraction of sources is not affected by this ambiguity. The second ambiguity results in the estimated sources being multiplied by an arbitrary amplitude factor c_i. But the relative amplitude of the waveform point and wavelet coefficients is invariable. Thus, for the purpose of feature extraction, it is not affected by the ambiguities of BSS analysis.

3 Determining the number of sources and selecting significant observations for BSS analysis

3.1 Modified Gerschgorin disk estimator method for determining the number of sources

The number of sources has to be determined before doing BSS analysis. In practice, since the number of sources is usually unknown, the number of observed signals has to be big enough. This means that there should be as many microphones as possible. The hypothesis testing method, based on the confidence interval of the noise eigenvalue, can be used to determine the number of sources. But since a threshold value must be decided subjectively, this method is not credible for real application. Thus, methods that are free of subjective judgment are sought. The Akaike information criterion (AIC) method, the minimum descriptive length (MDL) method and the Gerschgorin disk estimator (GDE) method are effective for estimating the source number. Since the modified GDE method is a model-independent approach and is effective for both non-Gaussian and non-white noise models, we apply modified GDE in this paper to determine the number of sources.

The modified GDE method exploits the Gerschgorin radii of the transformed covariance matrix to determine the number of sources. By performing the unitary transformation on the estimated covariance matrix, the Gerschgorin radii $r_i (i = 1, \dots N)$ of the transformed covariance matrix $\boldsymbol{Q}$ with element $q_{ij} (i, j = 1, \dots, N)$ are calculated as follows:

$$r_i = \sum_{\substack{j=1 \\ j \neq i}}^{N} |q_{ij}| \text{ for } i = 1, \dots, N \tag{5}$$

The GDE criterion for estimating the number of sources is defined as [15]:

$$\mathrm{GDE}(k) = r_k - \frac{C(n)}{N-1} \sum_{i=1}^{N-1} r_i \tag{6}$$

where k is an integer in the closed interval $[1, N-2]$, and $C(n)$ is a non-increasing, adjustable factor function (between 0 and 1). For the modified GDE method, N different unitary transformations are performed and the averaged criterion is written as:

$$\mathrm{MGDE}(k) = \frac{1}{N} \sum_{i=1}^{N} \mathrm{GDM}_i(k) \tag{7}$$

where $\mathrm{GDE}_i(k)$ is a GDE criterion for the ith transformed covariance matrix. If $\mathrm{MGDE}(k)$ is evaluated from $k = 1$, the number of sources is determined as $k - 1$ (i.e. $M = k - 1$) when the first non-positive value of $\mathrm{MGDE}(k)$ is reached for $k \in \{1, N-1\}$.

3.2 Partial singular value analysis technique for selecting significant observations

In an acoustic-based monitoring process, the number of observations is always larger than the number of sources. While the number (N) of observations is no less than the number (M) of sources, the source separation can be achieved theoretically via any combination of observations. It is obvious that the computational complexity can be reduced by using M observations for BSS analysis. Moreover, in practice the influence of noise on the observations is different. Therefore, it is interesting that M significant observations are selected for BSS analysis. In the process of data acquisition, the observations that are close to the real source usually possess smaller noise interference, and are considered to be significant. Under this criterion, the partial singular value analysis method is developed for choosing these observations.

The partial singular value analysis method chooses significant observations via weighting the contribution of an observation to the singular value of the spectral density matrix of observations [14]. The spectral density matrix of observations is denoted as $\boldsymbol{P_X}(f)$, and its singular value decomposition is expressed as:

$$P_X = V_X \Lambda_X V_X^H \tag{8}$$

where V is a unitary matrix and the singular value matrix $\boldsymbol{\Lambda}_X$ is constituted by singular value $\sigma_i (i = 1, \dots, N)$, as follows:

$$\boldsymbol{\Lambda}_X = \begin{pmatrix} \sigma_1 & & & \\ & \sigma_2 & & \\ & & \ddots & \\ & & & \sigma_N \end{pmatrix} \tag{9}$$

The matrix $\boldsymbol{\Lambda}_X$ indicates some characteristics of independent sources and it is known that the number of sources can be determined by testing the number of the non-zero, singular-values under a noise-free condition. Thus, it is reasonable that the singular values $\sigma_i (i = 1, \dots, N)$ of matrix $\boldsymbol{P}_X(f)$ can be considered as weight for checking the power ratio of independent sources contained in the observed signal vector $\boldsymbol{X}(t)$.

While the $q1$th observed signal $x_{q1}(t)$ is removed from the observation vector $\boldsymbol{X}(t)$, the modified observation signal vector $\boldsymbol{X}_{\cdot q1}(t)$ is written as:

$$\boldsymbol{X}_{\cdot q1}(t) = \left(x_1(t), \cdots, x_{q1-1}(t), 0, x_{q1+1}(t), \cdots, x_N(t)\right)^T \quad \text{for } q1 = 1, \dots, N \tag{10}$$

The spectral density matrix of $\boldsymbol{X}_{\cdot q1}(t)$ is denoted as $\boldsymbol{P}_{X_{\cdot q1}}(f)$, and its singular value decomposition is given as:

$$\boldsymbol{P}_{X_{\cdot q1}} = \boldsymbol{V}_{\cdot q1}\boldsymbol{\Lambda}_{\cdot q1}\boldsymbol{V}_{\cdot q1}^H \tag{11}$$

The diagonal elements $\sigma_{i \cdot q1} (i = 1, \dots, N)$ of the singular value matrix $\boldsymbol{\Lambda}_{\cdot q1}$ are defined as the first order partial singular values. So, the first order partial singular values indicate the power ratio of independent sources contained in the modified signal $\boldsymbol{X}_{\cdot q1}(t)$. Then, the $q2$th observed signal$x_{q2}(t)(1 \le q2 \le N, q2 \ne q1)$ is removed from $\boldsymbol{X}_{\cdot q1}(t)$ and the modified observation vector is denoted as $\boldsymbol{X}_{\cdot q1 \cdot q2}(t)$. The spectral density matrix of $\boldsymbol{X}_{\cdot q1 \cdot q2}(t)$ is denoted as $\boldsymbol{P}_{X_{\cdot q1 \cdot q2}}(f)$, and its singular value matrix is denoted as $\boldsymbol{\Lambda}_{\cdot q1 \cdot q2}$. The diagonal elements $\sigma_{i \cdot q1 \cdot q2} (i = 1, \dots, N)$ of matrix $\boldsymbol{\Lambda}_{\cdot q1 \cdot q2}$ are defined as the second order partial singular values. So, the second order partial singular values indicate the power ratio of independent sources contained in the modified signal $\boldsymbol{X}_{\cdot q1 \cdot q2}(t)$. Similarly, any order partial singular value can be calculated in this way.

The $\text{sum}(\Delta\sigma_{\cdot q1})(q1 = 1, \dots, N)$ is defined as the summation of the decrement of singular values while signal $x_{q1}(t)$ is removed, and it is written as the trace difference between matrix $\boldsymbol{\Lambda}_{\cdot q1}$ and$\boldsymbol{\Lambda}_X$. For instance:

$$\text{sum}(\Delta\sigma_{\cdot q1}) = Tr(\boldsymbol{\Lambda}_X) - Tr(\boldsymbol{\Lambda}_{\cdot q1}) \text{ for } q1 = 1, \dots, N \tag{12}$$

The $\text{sum}(\Delta\sigma_{\cdot q1})$ indicates the contribution of signal $x_{q1}(t)$ to singular values of the spectral density matrix $\boldsymbol{P}_X(f)$. The more significant that removed signal is, the more the singular values will be reduced. Similarly, the $\text{sum}(\Delta\sigma_{\cdot q1 \cdot q2})$ is written as the trace difference between matrix $\boldsymbol{\Lambda}_{\cdot q1 \cdot q2}$ and $\boldsymbol{\Lambda}_X$. For instance:

$$\text{sum}(\Delta\sigma_{\cdot q1 \cdot q2}) = Tr(\boldsymbol{\Lambda}_X) - Tr(\boldsymbol{\Lambda}_{\cdot q1 \cdot q2}) \quad \text{for } q2 = 1, \dots, N \text{ and } q2 \ne q1 \tag{13}$$

Other sum(•) can be also calculated in this way. The sum(•) is an optimal criterion for the selection of the most significant signals among all observations.

First, the observation $x_{q1}(t)$ that results in the corresponding sum $(\Delta\sigma_{\cdot q1})$ which has the largest value is selected as a key signal. The next key signal, assumed to be the $x_{q2}(t)$, is decided by the largest $\text{sum}(\Delta\sigma_{\cdot q1 \cdot q2})$. This procedure could be repeated M times, until M observations are completely determined. Basically, these observations are an optimal set for BSS analysis among all candidate observations.

4 Time-frequency separation algorithm for identifying mixing matrix and recovering wavelet coefficients

There are various BSS algorithms developed for retrieving the time waveforms of various sources, such as non-Gaussian sources, Gaussian sources, stationary sources and non-stationary sources. In an acoustic-based diagnosis field, the source signals are usually non-stationary and more attention is paid to recovering the wavelet coefficients related to fault features. Therefore, as a suitable algorithm for the separation of non-stationary signals, the time-frequency separation (TFS) algorithm is proposed to identify the mixing matrix of model [9]. Consequently, the wavelet coefficients of sources are obtained via the traditional source-identification method.

The TFS algorithm belongs to the family of "closed-form" BSS algorithms and it is based on a joint diagonalisation of a combined set of spatial time-frequency distributions matrix. The spatial time-frequency distributions matrix of the source signal vector $\boldsymbol{S}(t)$ is defined as:

$$\boldsymbol{D}_S(t, f) = \sum_{l=-\infty}^{\infty}\sum_{m=-\infty}^{\infty} \phi(m, l)\boldsymbol{S}(t + m + l) \boldsymbol{S}^*(t + m - l)e^{-j4\pi f t} \tag{14}$$

where t and f represent the time index and the frequency index respectively, and superscript * denotes conjugate transpose. The kernel $\phi(m, l)$ characterizes the distribution and is a function of both the time and lag variables. Since the off-diagonal elements of matrix $\boldsymbol{D}_S(t, f)$ are cross terms of $\boldsymbol{D}_S(t, f)$, this matrix is diagonal for each $t - f$ point that corresponds to a true power concentration, such as signal auto-term. Under the linear data model of (1), the spatial time-frequency distributions matrix of observations is given by:

$$\boldsymbol{D}_X(t, f) = \boldsymbol{A}\boldsymbol{D}_S(t, f)\boldsymbol{A}^H \tag{15}$$

where superscript H denotes the Hermite transpose.

The first processing step of the TFS algorithm consists of obtaining a whitened signal $\boldsymbol{Y}(t)$. This is achieved via apply a whitening matrix $\boldsymbol{W}$ to the whitened signal $\boldsymbol{X}(t)$. For instance:

$$\boldsymbol{Y}(t) = \boldsymbol{W}\boldsymbol{X}(t) = \boldsymbol{W}\boldsymbol{A}\boldsymbol{S}(t) \tag{16}$$

The whitening matrix $\boldsymbol{W}$ satisfies:

$$\lim_{T\to\infty} \frac{1}{T} \sum_{t=1}^{T} \boldsymbol{W}\boldsymbol{X}(t)\boldsymbol{X}^{*}(t)\boldsymbol{W}^{H} = \boldsymbol{W}\boldsymbol{R}_{X}(0)\boldsymbol{W}^{H} = \boldsymbol{W}\boldsymbol{A}\boldsymbol{A}^{H}\boldsymbol{W}^{H} = \boldsymbol{I} \tag{17}$$

where $\boldsymbol{R}_{X}(0)$ is the covariance matrix of observed signals. It is noted for above equation that we take advantage of the second ambiguity of BSS analysis by treating the source signals as if they have unit power so that the dynamic range of the sources is accounted for by the magnitude of the corresponding columns of mixing matrix $\boldsymbol{A}$. This is the covariance matrix of source signals that satisfies $\boldsymbol{R}_{S}(0) = \boldsymbol{I}$. From the above equation, we know that $\boldsymbol{W}\boldsymbol{A}$ is a unitary matrix, and is defined by:

$$\boldsymbol{U} \triangleq \boldsymbol{W}\boldsymbol{A} \tag{18}$$

Therefore, the whitening procedure converts the problem of identifying a mixing matrix $\boldsymbol{A}$ into a unitary matrix $\boldsymbol{U}$.

Similar to Eq. 8, the spatial time-frequency distributions matrix $\boldsymbol{D}_{Y}(t, f)$ of a whitened signal is given as:

$$\boldsymbol{D}_{Y}(t, f) = \boldsymbol{W}\boldsymbol{D}_{X}(t, f)\boldsymbol{W}^{H} = \boldsymbol{U}\boldsymbol{D}_{S}(t, f)\boldsymbol{U}^{H} \tag{19}$$

Since matrix $\boldsymbol{U}$ is unitary (i.e. $\boldsymbol{U}^{-1} = \boldsymbol{U}^{H}$) and $\boldsymbol{D}_{S})and(t, f)$ is diagonal, the unknown unitary matrix can be obtained as a unitary diagonalising matrix of a whitened spatial time-frequency distributions matrix for some $t - f$ points corresponding to a signal autoterm. In this case, a unitary matrix $\hat{\boldsymbol{U}}$ is obtained as joint diagonalizer of the set $\{\boldsymbol{D}_{Y}(t_i, f_i) \,|i = 1, \dots, K\}$. Here, the joint diagonaliser of the set $\{\boldsymbol{D}_{Y}(t_i, f_i) \,|i = 1, \dots, K\}$ means minimizing the following joint diagonalisation criterion function $C(\boldsymbol{U})$ over the set of all unitary matrices:

$$C(\boldsymbol{U}) = \sum_{i=1}^{K} \mathrm{off}(\boldsymbol{U}^{H}\boldsymbol{D}_{Y}(t_i, f_i)\boldsymbol{U}) \tag{20}$$

where "off" is the sum of non-diagonal elements of a matrix, which indicates the extent of diagonalisation of a matrix. It is defined as:

$$\mathrm{off}(\boldsymbol{Q}) = \sum_{1\le i\ne j\le M} q_{ij}^{2} \tag{21}$$

where q_{ij} is the element of matrix $\boldsymbol{Q}$. The joint diagonalisation criterion function $C(\boldsymbol{U})$ is usually served as a contrast function for identification.

While estimator $\hat{\boldsymbol{U}}$ is obtained via minimizing the contrast function $C(\boldsymbol{U})$, BSS becomes a common source-identification problem. The wavelet transform $\boldsymbol{W}_{Y}(a, b)$ of whitened signals $\boldsymbol{Y}(t)$ is defined as:

$$\boldsymbol{W}_{Y}(a, b) = |a|^{-\frac{1}{2}} \int_{R} \boldsymbol{Y}(t)\psi^{*}\left(\frac{t-b}{a}\right) \mathrm{d}t \tag{22}$$

where $\psi(t)$ is the basic wavelet function. The wavelet transform is applied to Eq. 16. From Eq. 18, consequently, the wavelet transform $\boldsymbol{W}_{S}(a, b) = \left(W_{s_1}(a, b), \cdots, W_{s_M}(a, b)\right)^{T}$ of sources are obtained as follows:

$$\hat{\boldsymbol{W}}_{S}(a, b) = \hat{\boldsymbol{U}}^{H}\boldsymbol{W}_{Y}(a, b) \tag{23}$$

Thus, the wavelet coefficients of each source are successfully recovered from observations and the sound features can be obtained via reconstructing the wavelet coefficients. The purified sound signal or symmetrised dot pattern can be used to make mechanical fault diagnosis even in mutual interference condition of multi-sources.

5 Feature separation of machine sound signals

To check the availability of the second order blind identification (SOBI) method of spectrum separation version, experimental research was done in a semi-anechoic chamber. The sound sources are set up as two motors. Three microphones are placed to record

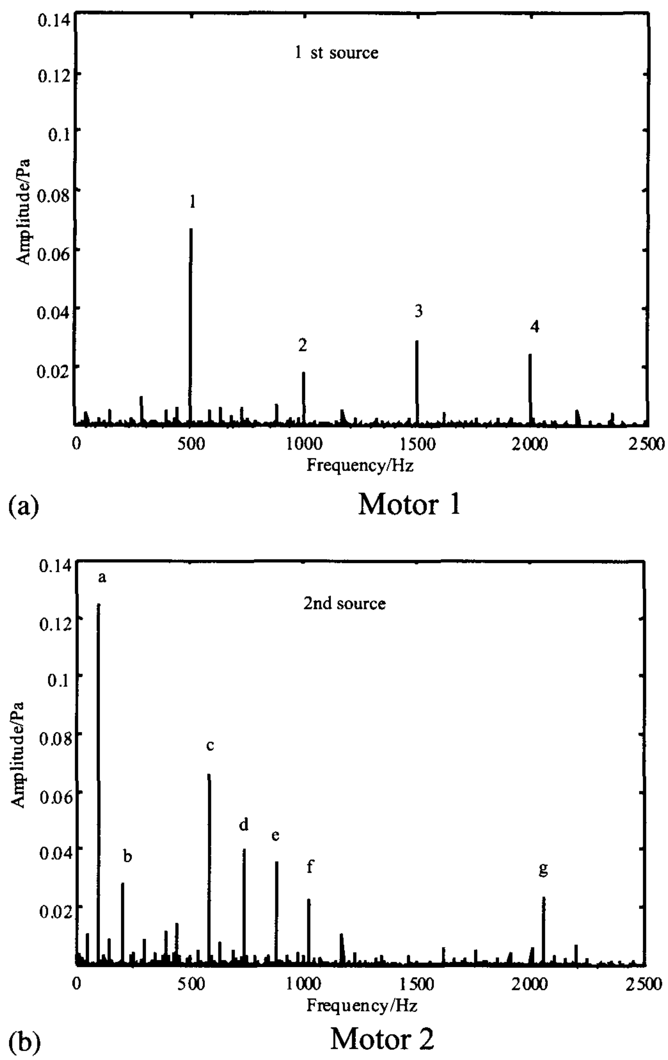

Fig. 2. The power spectra of sources

sound signals. The position map is shown in Fig. 1. For data acquisition, 65 536 samples per channel are stored at a sampling rate of 5 kHz.

The first step in the experiment was to record the individual source signal under the condition of keeping only one motor in working condition. The measured spectra of two motors are shown in Fig. 2. It is obvious that each source has distinct features. For example, the 500 Hz component and its harmonics (which is marked as 1,2,3 and 4) dominate the spectrum of the first source, as shown in Fig. 2a, and the 100 Hz, 200 Hz, 588 Hz, 734 Hz, 880 Hz, 1020 Hz and 2055 Hz harmonic components (which are marked as a, b, c, d, e, f and g) dominate the spectrum of the second source, as shown in Fig. 2a.

Then, we let the two motors run simultaneously and the sound signals are recorded with three microphones. The spectra of mixing signals are shown in Fig. 3. It can be seen that the features of the original spectra are mixed in all spectrum received, that is, the individual features of the motor cannot be distinguished easily.

Therefore, BSS method is applied to separate the two sources. Firstly, the number of sources should be determined. According to the discussion in Sect. 3, the singular-value analysis method is used. The calculating result for singular-value matrix is received as that $\boldsymbol{\Sigma}_X = \mathrm{diag}\,(0.1478,\ 0.1241,\ 0.0296)$, where diag(•) means diagonal matrix. As can be seen clearly that the 3rd value in singular-value matrix is relatively much smaller. Therefore, the number of sources is considered to be two. This means only the real number of sources are considered.

Next, the partial singular-value analysis is introduced to reduce the influence of the ill-conditioned problem on the separated results. The first order partial singular-value of spectral density matrix $\boldsymbol{P}_{X_k}(f)$ is obtained; that is, $\mathrm{sum}(\Delta\sigma_1) = 0.1056$, $\mathrm{sum}(\Delta\sigma_2) = 0.0769$, and $\mathrm{sum}(\Delta\sigma_3) = 0.1190$. It can be seen that the $\mathrm{sum}(\Delta\sigma_1)$ and $\mathrm{sum}(\Delta\sigma_3)$ are the two largest values among $\mathrm{sum}\ (\Delta\sigma_k)$ $(k = 1, 2, 3)$. This means that the 1st and the 3rd measuring signals are more significant. Therefore, these two measuring signals are selected for BSS analysis. The separated spectra are achieved via the spectral version of the SOBI algorithm, and the results are shown in Fig. 5.

Comparing the separated results with its originals, it is easily found that there exists a scaling factor between the separated sources and the original sources. But this does not affect the identification to the features. As can be seen in Fig. 4a, the main features of the 1st separated spectrum will match the 1st source (motor 1). This means that the first source is successfully recovered since the harmonic components (1), (2), (3) and (4) are almost same in features, even though the harmonics (d) and (e) of the 2nd source still appear here, as shown in Fig. 2. The 2nd separated source possesses the harmonic components (a), (b), (c), (d), (e), (f) and (g), as shown in Fig. 4. The influence of the harmonics (1), (2), (3) and (4) of the 1st source is significantly reduced. The separated result matches with the 2nd source very well. Therefore, in general, the overall quality of the separation can be evaluated as satisfactory in terms of feature separation.

Finally, to further prove that the 1st and 3rd measuring signals are more significant for BSS analysis, the 1st and 2nd meas-

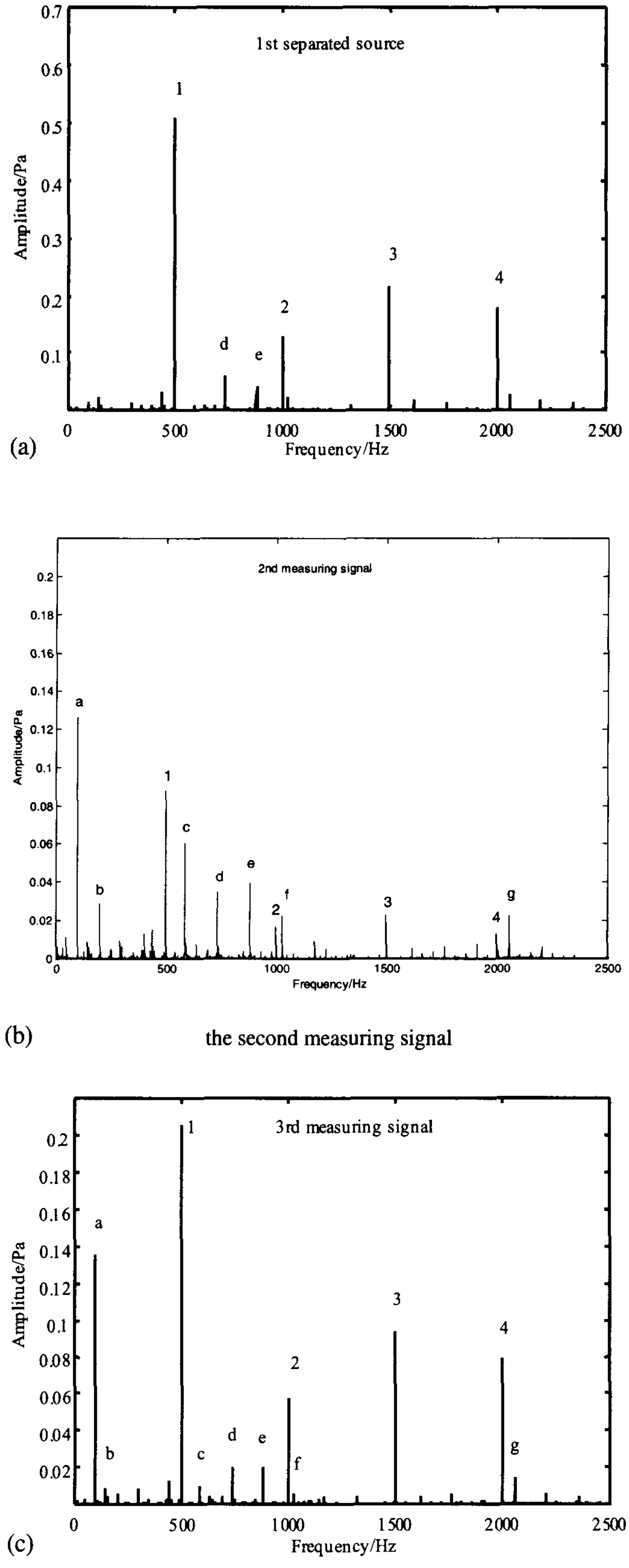

Fig. 3a–c. The power spectra of measuring signals **a** the first measuring signal **b** the second measuring signal **c** the third measuring signal

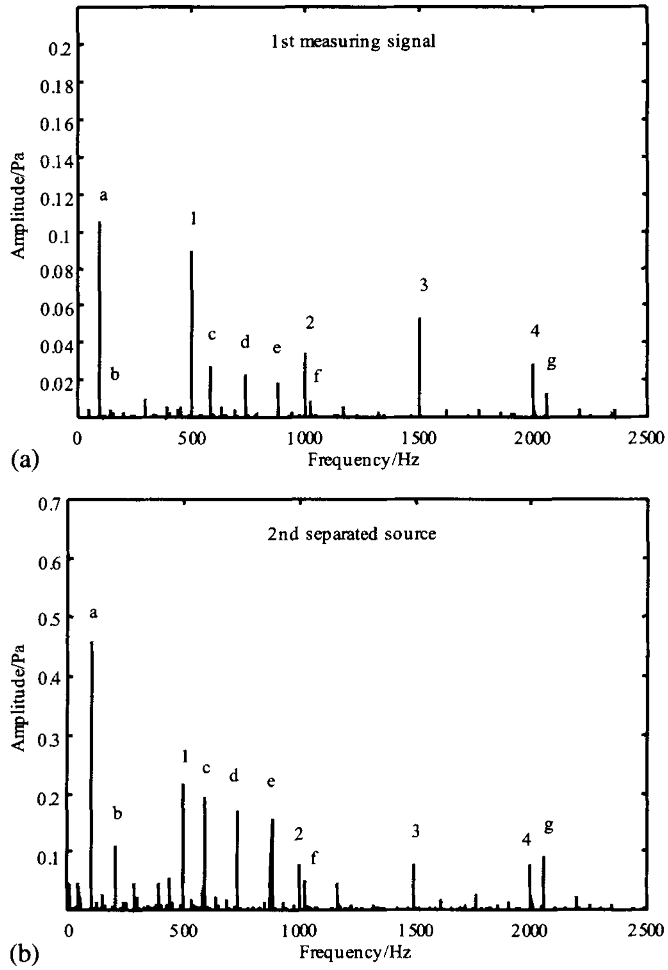

Fig. 4a,b. The separated power spectra based on the 1st and 3rd measuring signals **a** the first separated source **b** the second separated source

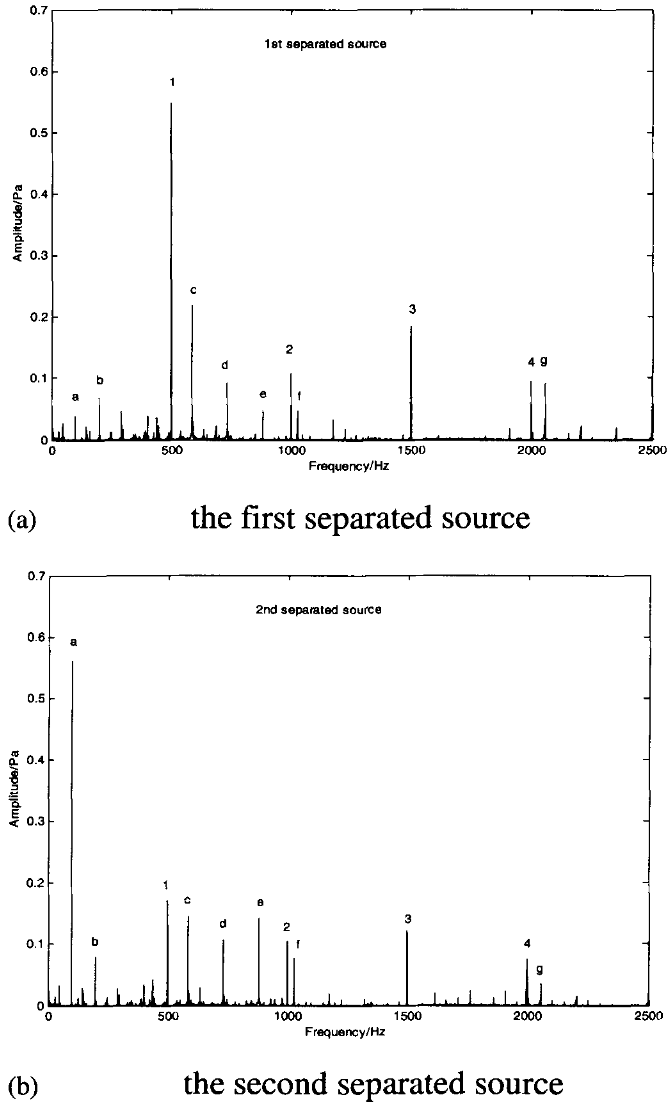

Fig. 5a,b. The separated power spectra based on the 1st and 2nd measuring signals **a** the first separated source **b** the second separated source

uring signals are selected to estimate the spectra of sources. The separated spectra are also achieved via the spectral SOBI algorithm and the results are shown in Fig. 5. Here, it can be seen that the mutual interference of sources becomes stronger. The quality of separation is inferior to the quality of the above. The same trend exists when the 2nd and the 3rd measuring signals are selected to estimate the spectra of sources.

The experiment was conducted in a semi-anechoic chamber to reduce sound reflection. The monitored system consists of two motors. The motors radiate machine sound and are considered to be sound sources. Three microphones are placed to record sound signals. The plan position map of monitored system and measuring microphones is shown in Fig. 2.

While two motors run simultaneously, the machine sounds are disrupt each other and the signal received by each microphone is the contribution of two sources. Sound interference is inevitable in the process of acoustic measuring. Changing the measuring location will change the mixing coefficients of mixing model, but in practice there is a very limited potential of reducing sound interference by changing the measuring location. BSS technique separates source without resorting to the mixing coefficient. This method does not depend on the mixing matrix and it is used to separate machine sound from observations.

We have 65 536 samples of signals at 15 kHz. Each of these is resampled (after low-pass filtering) at a frequency of 5000 Hz to highlight the desired frequency band and to ensure that the mixing model is as instantaneous as possible.

In order to check the separated results, each motor run individually at first. The spectra of two motors are shown in Fig. 3. It is obvious that each source has distinct features. For the first source, the 500 Hz harmonic component and its times (which are marked as 1,2,3 and 4) dominate the spectrum; and in the case of the second source, the 100 Hz, 200 Hz, 588 Hz, 734 Hz, 880 Hz, 1020 Hz and 2055 Hz harmonic components (which is marked as a, b, c, d, e, f and g) dominate the spectrum.

Then we let the two motors run simultaneously, the machine sounds being recorded with three microphones. The spectra are shown in Fig. 4. It can be seen that the spectra are the mixings of the two sources and the features cannot be distinguished.

The sources are separated with BSS method. First, to determine the number of sources, the singular value analysis of the spectral density matrix is carried out and the singular value matrix $\boldsymbol{\Sigma}_X$ is constructed as $\boldsymbol{\Sigma}_X = \mathrm{diag}\,(0.1478,\ 0.1241,\ 0.0296)$, where diag(•) means a diagonal matrix. It is obvious in singular value matrix that the 3rd singular value is relatively smaller than the others. Therefore, the number of sources is considered to be two. This consists with the real number of sources.

Second, to reduce the influence of the ill-conditioned problem on separated results, a partial singular value analysis is carried out. The first order partial singular value of spectral density matrix $\boldsymbol{P}_{X_k}(f)$ is calculated, and the $\mathrm{sum}(\Delta\sigma_k)$ $(k = 1, 2, 3)$ are obtained as $\mathrm{sum}(\Delta\sigma_1) = 0.1056$, $\mathrm{sum}(\Delta\sigma_2) = 0.0769$, and $\mathrm{sum}(\Delta\sigma_3) = 0.1190$. It can be seen that the $\mathrm{sum}(\Delta\sigma_1)$ and $\mathrm{sum}(\Delta\sigma_3)$ are the two largest values among $\mathrm{sum}(\Delta\sigma_k)$ $(k = 1, 2, 3)$. This means that the 1st and the 3rd observations are more significant. Therefore, those two observations are selected for BSS analysis.

The separated spectra are achieved via the spectral SOBI algorithm. Results are shown in Fig. 5. From the separated amplitudes, it is evident that there exists a scaling factor between the separated sources and the original sources, but this does not affect the separation of features. In comparing these results to Fig. 3, it is obvious that the main features of each motor are successfully separated. The harmonics (1), (2), (3) and (4) are well recovered to the 1st separated source. Even though the harmonics (d) and (e) of the 2nd source are also assigned to the 1st separated source, they are very weak and have little influence on the separated result. The 2nd separated source possesses the harmonics (a), (b), (c), (d), (e), (f) and (g). The influence of the harmonics (1), (2), (3) and (4) of the 1st source is significantly reduced. The separated result is consistent in the case of the 2nd source as well. Compared to the 1st separated result, the remainder of the 1st source exists in the 2nd separated source. The may be caused by the fact that the 1st source possesses more power in observations and as such, its influence on the separated results becomes stronger. In summary, the overall quality of separation can be evaluated as being satisfactory with respect to feature separation.

Finally, to prove that the 1st and the 3rd observations are more significant for BSS analysis, the 1st and the 2nd observations are selected to estimate the spectra of sources. The separated spectra are also achieved via the spectral SOBI algorithm, and the results are shown in Fig. 5. It can be seen that the mutual interference of sources becomes strong. In this case, the quality of separation is of inferior quality. The same trend exists when the 2nd and the 3rd observations are selected to estimate the spectra of sources.

6 Conclusions

Machine sound signals can be used in fault diagnosis. But the mutual interference of sound signals could reduce the SNR of the observed signals, since the feature sound may be hidden. This paper suggests the BSS technique as an effective method for recovering the feature sound signals from observed signals. In the application of the BSS algorithm, the number of sources must be determined. We were successful in applying the modified Gerschgorin disk estimator method to determine the number of sources. The partial singular value analysis method is developed and is proved to be effective for selecting significant observations for BSS analysis. Finally, the time-frequency separation algorithm is shown to be useful in the recovery of the wavelet coefficients of sources. The reconstructed wavelet coefficients can be used to make fault diagnosis.

Acknowledgement This work was supported by the National Natural Science Foundation of China (Approved No. 50075052) and the Beijing High-Technology Laboratory of Photoelectric Conversion Equipment and Noise Signal Processing (Beijing, China). The authors also thank the anonymous reviewers for many useful remarks.

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