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Improved Singular Value Decomposition (TopSVD) for Source Number Estimation of Low SNR in Blind Source Separation

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ABSTRACT An improved singular value decomposition based on Toeplitz (TopSVD) is proposed to solve the problem of inaccurately estimating source numbers under the condition of a low signal-to-noise (SNR) ratio for blind source separation. First, Toeplitz modifies the covariance of the received data, and singular value decomposition is used to estimate the number of signal sources. The advantages of TopSVD over traditional approaches are demonstrated by simulated signals. The results demonstrate that the proposed method can be used to estimate the number of coherent sources under low SNR conditions; at the same time, it can significantly improve the accuracy of source number estimation under the conditions of a low SNR and coherent signal source with the simple algorithm.

INDEX TERMS Blind source separation, singular value decomposition, toeplitz, low SNR.

I. INTRODUCTION

Blind source separation occurs in the case of unknown source signals and mixed processes, and the source signal can be recovered effectively only by the observing signal [1], [2]. With the development of science, blind source separation is often applied in the field of mechanical equipment fault diagnosis [3]–[5]. Before blind source separation, one of the important preconditions for blind source separation is to estimate the number of source signals accurately and effectively [6]–[8].

Many scholars have put forward methods of estimating the number of sources and have achieved good results in practice, such as spatial smoothing rank (SSR) [9], [10], information theory (AIC, MDL) [11], [12], singular value decomposition (SVD) [13]–[15], among others. The AIC algorithm has better performance under low SNR conditions; however, due to the large number of coherent signals in the process of signal transmission and reception, the source signal and noise signal influence each other, invalidating the information theory method. Therefore, decorrelation of the signal is performed before source number estimation. For the decorrelation of the observed signal, many algorithms have been proposed [16], [17]. However, the singular value decomposition method proposed in this paper is obtained by reducing the degree of freedom. Although the smoothed rank sequence method can estimate the number of coherent sources, it also requires a higher SNR. When the SNR is low, the performance is not ideal. At the same time, although there aremany theories and methods regarding estimating the number of sources in the literature [18]–[20],little research has been done on application of the source number estimation method to solve the problem of mechanical system engineering. Therefore, in this paper, an improved eigenvalue decomposition algorithm is proposed for the estimation of mechanical system source number under the condition of low SNR.The new algorithm combines the advantages of the traditional SVD algorithm and the Toeplitz algorithm, and is used to estimate the source number under the conditions of a low SNR and coherent signal source.The proposed method is called TopSVD.

II. SOURCE NUMBER ESTIMATION THEORY

A. SOURCE LINEAR SUPERPOSITION MODEL

The signals $S(t) = [s_1(t), \ldots, s_n(t)]^T$ are contained in n mechanical system source signals, so the observed signal $X(t) = [x_1(t), \ldots, x_m(t)]^T$ is obtained in m different sensors. Each observed signal is assumed to be a linear superposition of all source and noise signals $N(t) = [n_1(t), n_2(t,) \ldots n_m(t)]$ via a hybrid matrix $A = \{a_{ij}\}(m \times n)$. The observed mixed signal $X(t)$ can be described as follows:

$$x_i(t) = \sum_{j=1}^{n} a_{ij} s_j(t) + n_i(t)$$
$$i = 1, \ldots m; j = 1, \ldots n \quad (1)$$
$$X(t) = AS(t) + N(t) \quad (2)$$

$R = E[XX^T]$ is assumed to be the autocorrelation matrix of the observed mixed signal $X(T)$ (E is the expressed expectation function), and the eigenvalues satisfice $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_m$, $L(n)$ is a log likelihood function. The expressions are as follows for this calculation:

$$L(n) = \frac{(\lambda_{n+1}\lambda_{n+2}\ldots\lambda_m)^{1/(m-n)}}{1/(m-1)(\lambda_{n+1} + \lambda_{n+2} + \ldots + \lambda_m)} \quad (3)$$

Signal processing methods are based on linear superposition theory, and the central problem of principal component analysis is to choose the number of separated components that needs to be preserved. The M-dimension signal is projected onto the N-dimension ($n < m$) feature space, and compressing the spatial dimension of the redundant information is achieved while preserving all of the source information and determining the uncorrelated separated components. The number of separated components represents the number of the source signals in the observation signal to realize effective estimation of the number of source signals.

B. SINGULAR VALUE DECOMPOSITION (SVD) METHOD

For the covariance matrix R_x of the received data, the eigenvalue decomposition is performed as follows:

$$R_x = Q\Lambda Q^H \quad (4)$$

where Λ is a diagonal matrix composed of the eigenvalues $\{\lambda_1\lambda_2, \ldots\lambda_m\}$ of R_x. Every column vector of the eigenvector Q is a unit eigenvector corresponding to the eigenvalue, and the unit vectors are orthogonal to each other. It can be deduced that the eigenvalues of $R_X R_X^H$ derived by the characteristic decomposition are $\{\lambda_1^2, \lambda_2^2, \ldots\lambda_M^2\}$. That is,

$$R_X R_X^H = Q\Lambda Q^H (Q\Lambda Q^H)^H = Q\Lambda^2 Q^H \quad (5)$$

Therefore, the singular value of R_X defined by the singular value is $\{|\lambda_1|, |\lambda_2|, \ldots, |\lambda_M|\}$ because the singular value of the covariance matrix is the same as the absolute value of the eigenvalue. Therefore, the number of nonzero singular values is equal to the number of nonzero eigenvalues. It is assumed that $\tilde{R}_x$ is covariance matrix of the mixed signal with noise. By the mixed system model $X = AS + N$, the following can be calculated:

$$\begin{aligned}\tilde{R}_X &= \frac{XX^H}{L} = \frac{(AS+N)(AS+N)^H}{L} \\ &= \frac{ASS^HA^H + ASN^H + NS^HA^H + NN^H}{L} \\ &= R_X + R_N + \frac{A(SN^H) + (NS^H)A^H}{L}\end{aligned} \quad (6)$$

where $R_N \approx \sigma^2 I$, $\frac{SN^H}{L} \approx 0$, $\frac{NS^H}{L} \approx 0$, and then,

$$\tilde{R}_X = R_X + \sigma^2 I \quad (7)$$

where σ^2 is power of the noise.

If $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_k = \lambda_{k+1} \ldots = \lambda_M = 0$ is M eigenvalues of R_X and $\mu_1 \geq \mu_2 \geq \ldots \geq \mu_k \geq \mu_{k+1} \geq \ldots \geq \lambda_M \geq 0$ is M eigenvalues of $\tilde{R}_X$, $\mu_1 \approx \lambda_1 + \sigma^2$, $\mu_2 \approx \lambda_2 + \sigma^2, \ldots, \mu_k \approx \lambda_k + \sigma^2, \ldots, \mu_m \approx \lambda_m + \sigma^2$. Therefore, in the case of a high SNR, the main eigenvalue of the covariance matrix is equal to the number of signal sources.

The eigenvalues of the signal covariance matrix are arranged from high to low, that is, $\mu_1 \geq \mu_2 \geq \ldots \geq \mu_M \geq 0$; let $\lambda_k = \mu_k/\mu_{k+1}$, $(k = 1, 2, \ldots, M-1)$. h is the maximum eigenvalue of the covariance matrix and satisfies $\lambda_h = \max\ (\lambda_1, \lambda_2, \ldots, \lambda_{M-1})$.The eigenvalue decomposition method is simple and can be realized easily; however, the values are easily affected by the SNR and the number of sampling points. It is not suitable for coherent signal sources.

C. IMPROVEMENT OF SINGULAR VALUE DECOMPOSITION BASED ON TOEPLITZ

The essence of the Toeplitz method is to average the diagonal elements of the data covariance matrix. It can be calculated by the following two equations:

$$\tilde{r}(-n) = \frac{1}{M-n} \sum_{i=1}^{M-n} \tilde{r}_{i(i+n)} 0 \leq n < M \quad (8)$$
$$\tilde{r}_T(n) = \tilde{r}_T^*(-n) \quad (9)$$

where M is the number of sensors, $\tilde{r}_{ij}$ is the element of $\tilde{R}$, and $\tilde{r}_{Tij}(n) = \tilde{r}_T(i-j)$.

The covariance matrix obtained by Eq. (6) is as follows:

$$\tilde{R}_x = E[X(t)X(t)^H] \quad (10)$$

The elements of the data covariance matrix are as follows:

$$[\tilde{R}_x]_{ij} = E[x_i(t)x_j(t)^H] = R_{xx}(i-j) = R_{xx}^*(i-j) \quad (11)$$

where $\tilde{R}_x$ satisfies the following:

$$\tilde{R}_x = \begin{pmatrix} \tilde{R}_x(1) & \tilde{R}_x^*(2) & \tilde{R}_x^*(3) & \cdots & \tilde{R}_x^*(m) \\ \tilde{R}_x(2) & \tilde{R}_x(1) & \tilde{R}_x^*(2) & \cdots & \tilde{R}_x^*(m-1) \\ \tilde{R}_x(3) & \tilde{R}_x(2) & \tilde{R}_x(1) & \cdots & \tilde{R}_x^*(m-2) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \tilde{R}_x(m) & \tilde{R}_x(m-1) & \tilde{R}_x(m-2) & \cdots & \tilde{R}_x(1) \end{pmatrix} \quad (12)$$

According to Eq (10), in the ideal case of an independent signal source, $\tilde{R}_x$ has the properties of the Toeplitz matrix. In fact, $\tilde{R}_x$ is approximately estimated by $\tilde{R}_X = XX^H/L$. Due to the influence of the coherent signal source and low SNR, R is generally a diagonally dominant matrix that does not maintain the properties of the Toeplitz matrix.

The traditional eigenvalue decomposition method cannot estimate the coherent signal source and susceptibility to SNR, so the Toeplitz algorithm is used. The Toeplitz algorithm makes the true covariance matrix of the matrix be near to the eigenvalue by Toeplitz pre-treatment. That is,

$$\min_{R_T \in S_T} |R_T - R|$$

where S_T is the Toeplitz matrix set [21], [22].

Through the analysis of the above two algorithms, a new algorithm which combines the traditional SVD algorithm and the Toeplitz algorithm is proposed.The signals considered here are low SNR signals, and the number of signal sources can be obtained according to the steps of the following new algorithm:

1) Calculating the covariance matrix of data collected $\tilde{R}_X = XX^H/L$, it is known by Eq(6) that $\tilde{R}_X$ contains all the information of the signals.

2) $\tilde{R}_X$ contains all the information of the signals.Combining the conjugate symmetry of covariance matrix in Toeplitz algorithm, the observation matrix is reconstructed by Eq (12).

3) The eigenvalue decomposition of the reconstructed matrix is calculated. Ideally, the number of singular values of the reconstructed matrix is m.

4) Calculating the ratio between adjacent singular values. Let $\lambda_k = \mu_k/\mu_{k+1}$, $(k = 1, 2, ..., M - 1)$. If p satisfices $\lambda_p = \max(\lambda_1, \lambda_2, ..., \lambda_{M-1})$. The number of signal source is equal to p.

III. SIMULATION ANALYSIS

The gear is the key part of rotating machinery, and the gear signal is a non-stationary signal source. Amplitude modulation is common in gear faults, and its vibration signal model is as follows:

$$s(t) = \sum_{k=1}^{N} A_k(t) \cos(2\pi k f_m t + \phi_k)$$

where f_m is the meshing frequency, and N is the order of harmonic components. $A_k(t)$ and ϕ_k are the amplitude and phase of harmonic components, respectively.

To verify the validity of the algorithm, three simulation experiments are carried out. The fault signal of the gear is simulated by the amplitude modulation signal. The first simulation experiment is to verify the accuracy of the algorithm in the case of a low SNR and independent incoherent signals by comparison. The second simulation experiment is to estimate the accuracy of the new algorithm in the case of coherent signals. Comparing the results of the experiments proves the validity of the solution. The third simulation verifies the sensitivity of the algorithm to the sampling points. To verify the sensitivity of the algorithm to SNR, the success ratio of the detection is defined as the ratio between the number of correct estimates and number of simulations.

A. OBSERVATION SIGNAL SIMULATION

The number of sensors is assumed to be six, and the sensors receive data from two fault source signal data sources. The number of sampling points is set 200 (that is, the mixed matrix A is 6 × 2 matrix, and the source signal S is a matrix of 2 × 200).The sampling frequency is set to 1500 Hz.

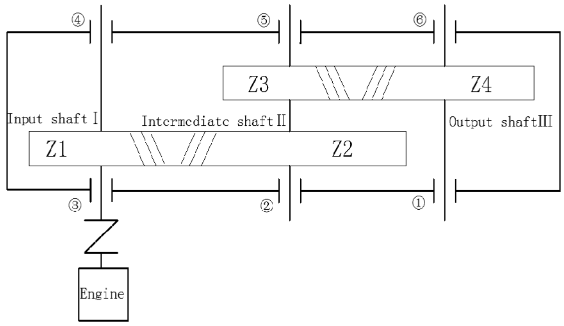

FIGURE 1. Gearbox model.

Gear failures are used as examples for simulation analysis, and the gearbox model is shown in Fig. 1. Z1 and Z4 are the sources of the fault, and ①–⑥ demonstrate the sensor placements.

The source signals S_1 and S_2 are sine signals and simulate the simple harmonic motion of a mechanical system. The effect of the mixed matrix A is to perform sinusoidal amplitude modulation of sine signal with a frequency of 10Hz. At the same time, random linear superposition for the modulation signal is performed to simulate the amplitude modulation characteristics of the gear fault signal. The mechanical structural and environmental noise with white noise signal are simulated as well.

$s_1(t)$ can be given as follows:

$$s_1(t) = \sin(200\pi t)$$

The coherent signal $s_2(t)$ is as follows:

$$s_2(t) = \sin(200\pi t + 0.1)$$

In the other case, the incoherent signal $s_2(t)$ can be given as follows:

$$s_2(t) = \sin(300\pi t)$$

The observation signal, which is added noise with the change of SNR, is modulated by the source signal.

Fig. 2 and Fig. 3 show the simulated signals in the case of coherent and incoherent for SNR = −10 dB.

B. PERFORMANCE ANALYSIS OF THE DETECTION SUCCESS RATE OF DIFFERENT ALGORITHMS

SNR is progressively changed by 1 dB from -14 dB to 0 dB, Monte Carlo experiments are carried on 100 times with different SNR values. The signal is defined as a weak signal when the SNR is between -14 dB and 0 dB.

The success rate of signals of the TopSVD algorithm and information theory method (including MDL algorithm and AIC algorithm) [11], [23], SSR algorithm and SVD algorithm [25] were compared and are commonly used in the literature in the case of incoherent signal source and correlated signal source. The accuracy of the commonly used

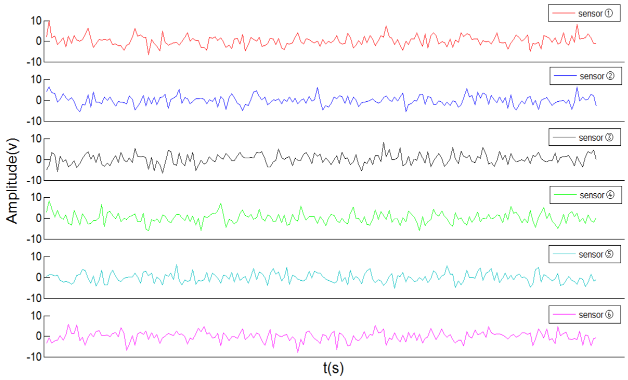

FIGURE 2. Observation signal of coherent signal when SNR is −10 dB.

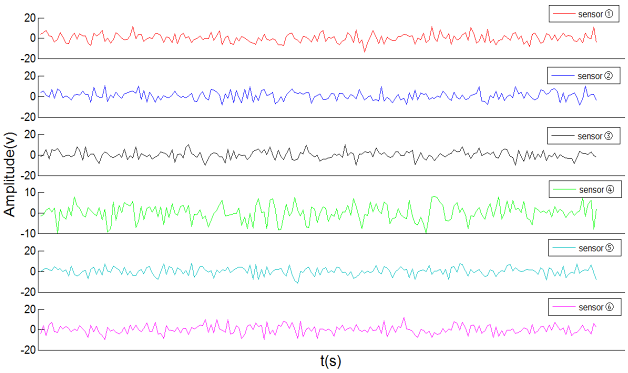

FIGURE 3. Observation signal of an incoherent signal when SNR is −10 dB.

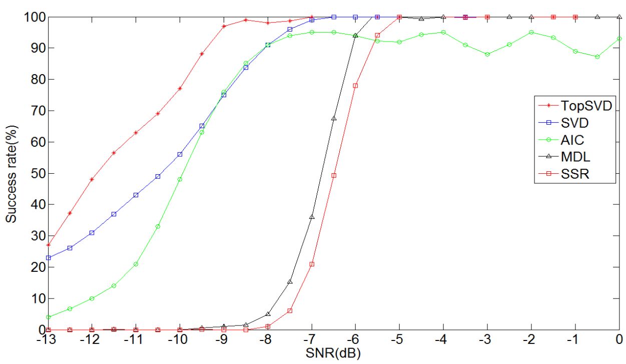

FIGURE 4. Change of the detection success rate of algorithms with SNR for an incoherent signal.

algorithms in the simulation experiments is consistent with the corresponding literature.

1) DETECTION SUCCESS RATE VERSUS SNR FOR THE INCOHERENT SIGNAL

In the simulation test, the acquired signals are independent incoherent signal sources, and several algorithms are affected by the SNR. The simulation results are shown in Fig. 4.

Fig. 4 presents the simulation results of the new algorithm, the AIC algorithm and MDL algorithm for estimation of the number of signal sources with a change of SNR. Compared

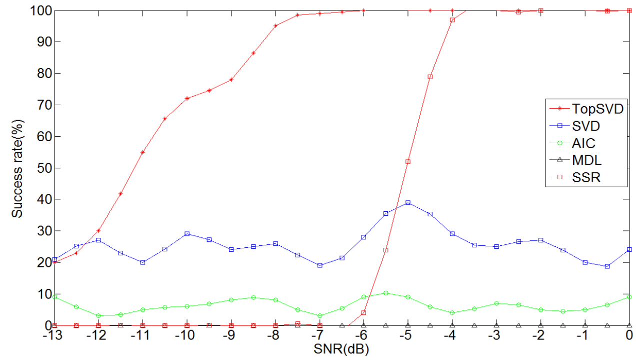

FIGURE 5. Change of the detection success rate of the algorithms with SNR for the coherent signal.

with the traditional SVD algorithm, the success rate of the new algorithm is always higher. In the case of a high SNR, the same as in the MDL algorithm, the new algorithm has good asymptotic consistency. However, in the case of a low SNR, especially when the SNR is less than -8 dB, the new algorithm still has a good success rate, but the success rate of other algorithms is not high.

2) DETECTION SUCCESS RATE VERSUS SNR FOR A COHERENT SIGNAL

In the simulation experiment, the acquired signal is a significant coherent signal source with a correlation coefficient of 0.8 and the SNR is from -13 dB to 0 dB. The signal source number estimation experiment uses the new algorithms, the AIC algorithm and MDL algorithm. The performance of the three algorithms is observed with the change of SNR, and the simulation results of the three algorithms are compared. The results are shown in Fig. 5.

As seen in Fig. 5, in the case of a coherent signal source, the success rate of the AIC, MDL and SVD algorithms is significantly reduced or even fails; however, for the new algorithm, its performance is still good at a low SNR and has the ability to decorrelate the coherent signals. Compared with the traditional SVD algorithm, especially when the SNR is larger than -12dB, the success rate of the new algorithm is obviously improved.

Comparing the curves of Fig. 4 with Fig. 5, when the signal source is coherent signal sources, the curve of the new algorithm is similar to that of the incoherent signal source.

3) SUCCESS RATE OF DETECTION VARIES WITH THE NUMBER OF SAMPLING POINTS

The detection success rate is less when using the SVD algorithm when the SNR is below -12 dB; however, the accuracy of the estimation is studied with the effect of sampling number when the SNR is -10 dB. The sampling points are from 10 to 3000 with a change of 20 points. one-hundred Monte Carlo experiment iterations are conducted for each sampling point.

In the simulation experiment, the signals are independent incoherent signal sources; the new algorithm, information

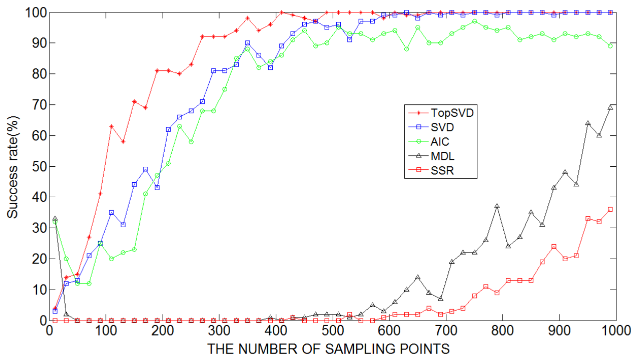

FIGURE 6. Change of the detection success rate with sampling points.

theory, SVD and SSR algorithms are used to estimate the number of signals.

The performance is observed of the five algorithms with the change of sampling points, and the simulation results of the five algorithms are compared. The simulation results are shown in Fig. 6.

The experimental results show that the new algorithm is better than other algorithms with a low SNR. The success rate of the new algorithm is consistently higher than the traditional SVD. In the case of fewer sampling points, the new algorithm shows some advantages. When the sampling point number is above 500, the success rate is close to 100%; however, the MDL and SSR algorithms fail in the case of few sampling points.

IV. CONCLUSIONS

In this paper, a new method to estimate the source number under the condition of a low SNR is presented. The simulation results show that the new algorithm is more accurate than the SVD, AIC, MDL and SSR algorithms under low SNR conditions. The new method can estimate the source number under the condition of a coherent signal source. Compared with the eigenvalue decomposition method, the success rate of the new algorithm is obviously improved. Compared with the SSR method with a higher SNR, the new algorithm better estimates the coherent signal source.

The source signal of a mechanical system has both coherent and incoherent signals, especially when a fault signal occurs in the system. The method proposed in this paper can effectively estimate the number of sources of the mechanical system over a certain range. For example, the source numbers are fewer and SNR is less than zero; however, in practice, due to the differences of fault types, fault locations and damage extent at different mechanical system locations, estimation of the source fault number from blind source separation requires further study.

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