

The Semi-blind Source Extraction Algorithm for Array Radar Signal

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Abstract—A semi-blind source extraction algorithm for noisy mixtures based on a linear predictor is proposed. The novel algorithm is firstly validated using the benchmark data and then is applied to extract array radar signal suffering from jamming interference. The results showed that the novel algorithm can effectively extract the target signal in radar echo. Thus, it has practical application prospect in array radar for increasing anti - jamming interference ability.

Index Terms—blind source extraction, cost function, AR autoregressive model parameter, array radar, jamming interference

I. INTRODUCTION

Blind source extraction (BSE) is a kind of blind source separation (BSS) technology [1] and has become a research hotspot in fields of signal processing in recent years. The purpose of BSE is to estimate a small subset of source signals, which are linear combination of all observed signals. Compared with BSS, BSE has more advantages, and has wider applications in many fields such as radar array signals processing [2], biomedical signal processing [3-4] and speech processing [5].

So far, a lot of BSE algorithms have been proposed. The typical algorithms included those based on the high order statistics (HOS) [6-7] and the second order statistics(SOS)[8]. Since the algorithms exploiting HOS have high computational load, the SOS-based algorithms is developed using priori knowledge about signal's temporal structure. However, the SOS algorithms based on linear predictors [9-12] required that all source signals are not correlated with each other and each source signal has different temporal structure.

Liu et al. [10] first proposed to extract the desired signal from mixtures when the AR model parameters of this signal were known in the noise-free case and then extended the results to the noisy case [13]. The algorithms of Liu et al. [10, 13] are classified as the mean cross prediction error (MCPE) algorithms that can extract the signal with minimal MSPE. In our previous work [14],

we proposed a BSE algorithm whose cost function can cater for the specific AR model parameters of desired signal. Our algorithm [14] is classified as the mean square cross prediction error (MSCPE) algorithm that can extract the signal with minimal MSCPE in the noise-free case. Our previous research results showed that the desired signal has always minimal MSCPE, but has not minimal MSPE.

Following Liu's research ideas [10, 13], we extend the algorithm in noise - free case in [14] to a novel BSE algorithm in the noisy case and apply the novel algorithm to extract array radar signal in this paper.

This paper is outlined as follows: In section II, the novel algorithm with new cost function in noisy case is introduced. The application feasibility of novel algorithm in array radar is analyzed in section III. The numerical results using the benchmark data and synthetic array radar signals are given and analyzed in section IV. The conclusions are finally drawn in section V.

II. ALGORITHM

In the noise-free case [14], we supposed that an observed stochastic signal vector \mathbf{x} with m -dimension is the linear mixture of an l -dimensional zero-mean and unit-variance vector \mathbf{s} , that is,

$$\mathbf{x}(n) = \mathbf{A}\mathbf{s}(n)$$

where $\mathbf{A} \in \mathbb{R}^{m \times l}$ is an unknown mixing matrix.

To suit for the ill conditioned case ($m > l$) and to make the novel algorithm be simpler and faster, the observed signals \mathbf{x} need to be pre-whitened, i.e., $\mathbf{H}\mathbf{E}\{\mathbf{x}\mathbf{x}^T\}\mathbf{H}^T = \mathbf{I}$, where $\mathbf{H} \in \mathbb{R}^{l \times m}$ is a pre-whitening matrix. However, we assume that \mathbf{x} has been pre-whitened and \mathbf{A} is an orthonormal matrix in this section for convenience.

On the basis of hypotheses above, we have the following signal models in the noisy case:

$$\underline{\mathbf{x}}(n) = \mathbf{A}\mathbf{s}(n) + \mathbf{v}(n) = \mathbf{x}(n) + \mathbf{v}(n) \quad (1)$$

where $\mathbf{x}(n) \in \mathbb{R}^m$ is the observed stochastic signal vector with m -dimension in the noisy case and $\mathbf{v}(n)$ is an unknown additive Gaussian white noise. Here we still assume that l is less than m .

The observation correlation matrix is calculated as follows:

$$\mathbf{C} = E\{\underline{\mathbf{x}}(n)\underline{\mathbf{x}}^T(n)\} = \mathbf{A}\mathbf{C}_s\mathbf{A}^T + \sigma^2\mathbf{I} \quad (2)$$

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Let λ_i and u_i ($i=1,2,\dots,m$) be respectively the eigenvalue and the orthonormal eigenvector of C corresponding to λ_i . The C can be decomposed as:

$$C=U\Sigma U^T$$

where $\Sigma = \text{diag}(\lambda_1, \lambda_2, \dots, \lambda_m)$ and $U = (u_1, u_2, \dots, u_m)$. Since l is less than m , the l no increasingly ordered eigenvalues can be expressed as:

$$\lambda_1 \geq \dots \geq \lambda_l > \lambda_{l+1} = \dots = \lambda_m = \sigma^2 \tag{3}$$

Thus, the subspaces of signal and noise are respectively

$$U_s = [u_1, \dots, u_l] \text{ and } U_v = [u_{l+1}, \dots, u_m] \tag{4}$$

The variance σ^2 of $v(n)$ can be estimated by the noise subspace and the observation data x can be projected into the signal subspace through $U_s^T x$.

For convenience, we also assume that A and $v(n)$ in (1) have been projected into the signal subspace in the noisy case.

In the presence of noise, the noise influences must be removed so that the resulting cost function remains same form with that in noise-free case [14].

The goal of BSE is to find a vector w that makes $y(n)=wTx(n)=wTAs(n)+ wTv(n)$ be an estimated source signal with additive noise. For the noise $v(n)$, we have

$$\begin{aligned} v(n) &= [v_1(n), v_2(n), \dots, v_l(n)]^T \\ E\{v_i(n)v_i(n)\} &= \sigma^2, (i=1,2,\dots,l) \\ E\{v_i(n)v_j(n)\} &= 0, (i \neq j, i, j=1,2,\dots,l) \\ E\{s_i(n)v_j(n)\} &= 0, (i, j=1,2,\dots,l) \end{aligned} \tag{5}$$

where σ^2 is the variance of noise. Assume that

$$\begin{aligned} y(n) &= w^T x(n) \\ \underline{y}(n) &= w^T \underline{x}(n) = y(n) + w^T v(n) = y(n) + u(n) \\ u(n) &= w^T v(n) \end{aligned} \tag{6}$$

Thus, the instantaneous noisy prediction error (PE) (denoted by $\underline{e}(n)$) can be calculated as:

$$\begin{aligned} \underline{e}(n) &= \underline{y}(n) - \mathbf{b}^T \underline{Y}(n) \\ \underline{Y}(n) &= [\underline{y}(n-1), \underline{y}(n-2), \dots, \underline{y}(n-p)]^T \end{aligned} \tag{7}$$

where \mathbf{b} is the AR parameters of a desired signal. Then, we utilize $\underline{e}(n)$ to estimate $e(n)$ (the PE in noise - free case in [14]) since $e(n)$ is unknown.

Let $e_u(n)$ denote the instantaneous PE of noise $u(n)$, that is,

$$\begin{aligned} e_u(n) &= \mathbf{b}^T \mathbf{u}(n) \\ \mathbf{u}(n) &= [u(n-1), u(n-2), \dots, u(n-p)]^T \end{aligned} \tag{8}$$

Then, we have:

$$\underline{e}(n) = e(n) + e_u(n) \tag{9}$$

The new cost function in noisy case is designed as:

$$\begin{aligned} J(\mathbf{w}) &= \min_w E^2 \{ (e(n)e(n-q)) \} \\ &= \min_w E^2 \{ (\underline{e}(n) - e_u(n))(\underline{e}(n-q) - e_u(n-q)) \}, 0 < q \leq p \end{aligned} \tag{10}$$

where q denotes error delay.

A novel BSE algorithm in noisy case can be constructed using eigenvalue decomposition (EVD) and the new cost function in (10). Assume that

$$\begin{aligned} \underline{z}(n) &= \left(\underline{x}(n) - \sum_{i=1}^p b_i \underline{x}(n-i) \right) \\ z_v(n) &= \left(v(n) - \sum_{i=1}^p b_i v(n-i) \right) \end{aligned} \tag{11}$$

By combining (6) and (11), we have:

$$\begin{aligned} \underline{z}(n) &= z(n) + z_v(n) \\ \underline{e}(n) &= \mathbf{w}^T \underline{z}(n) = \underline{z}(n)^T \mathbf{w} \\ e_v(n) &= \mathbf{w}^T z_v(n) = z_v(n)^T \mathbf{w} \end{aligned} \tag{12}$$

Assume that

$$\mathbf{Z}(q) = E\{z(n)z^T(n-q)\} \tag{13}$$

Thus, $\mathbf{Z}(q)$ can be expressed as follows:

$$\begin{aligned} \mathbf{Z}(q) &= E\{z(n)z^T(n-q)\} \\ &= E\{(\underline{z}(n) - z_v(n))(\underline{z}(n-q) - z_v(n-q))^T\} \\ &= E\{\underline{z}(n)\underline{z}^T(n-q)\} - E\{\underline{z}(n)z_v^T(n-q)\} \\ &\quad - E\{z_v(n)\underline{z}^T(n-q)\} + E\{z_v(n)z_v^T(n-q)\} \end{aligned} \tag{14}$$

Note that $z(n)$ is determined by the source signal and $z_v(n)$ is determined by noise. Further, we have:

$$\begin{aligned} E\{\underline{z}(n)z_v^T(n-q)\} &= 0 \\ E\{\underline{z}(n)z_v^T(n-q)\} &= E\{z_v(n)z_v^T(n-q)\} = \left(-b_q + \sum_{i=1}^{p-q} b_i b_{i+q} \right) \sigma^2 I \end{aligned} \tag{15}$$

$\mathbf{Z}(q)$ can be simplified as:

$$\begin{aligned} \mathbf{Z}(q) &= E\{\underline{z}(n)\underline{z}^T(n-q)\} - E\{z_v(n)z_v^T(n-q)\} \\ &= E\{\underline{z}(n)\underline{z}^T(n-q)\} - \left(-b_q + \sum_{i=1}^{p-q} b_i b_{i+q} \right) \sigma^2 I \end{aligned} \tag{16}$$

From (16), we can know that $\mathbf{Z}(q)$ is calculated using the observed data $\underline{x}(n)$ and AR model parameters \mathbf{b} of desired signal. Thus, the algorithm with new cost function in noisy case can finally be expressed as:

$$\begin{aligned} \underline{z}(n) &= \left(\underline{x}(n) - \sum_{i=1}^p \mathbf{b}_i \underline{x}(n-i) \right) \\ \mathbf{Z}(q) &= E\{\underline{z}(n)\underline{z}^T(n-q)\} - \left(-b_q + \sum_{i=1}^{p-q} b_i b_{i+q} \right) \sigma^2 \end{aligned} \tag{17}$$

$\mathbf{w} = \text{MINEVD}\{\mathbf{Z}(q)\mathbf{Z}^T(q)\} = \text{MINSVD}\{\mathbf{Z}(q)\}$ where the normalized eigenvector corresponding to the minimal eigenvalue of $\mathbf{Z}(q)\mathbf{Z}^T(q)$ is calculated by the *MINEVD* $\{\mathbf{Z}(q)\mathbf{Z}^T(q)\}$ and the normalized singular vector corresponding to the minimal singular value of $\mathbf{Z}(q)$ by the *MINSVD* $\{\mathbf{Z}(q)\}$.

III. APPLICATIONS IN ARRAY RADAR SUFFERING FROM JAMMING INTERFERENCE

The existing researches showed that the radar echo signals received by the array radar can be modeled as an

instantaneously mixed noisy signal. The difference between the desired target signals in radar echo and its transmitted signals mostly lies on time delay and frequency slide, and thus the AR model parameters of the desired target signals can be estimated using the transmitted signals. According to the above analysis, our novel algorithm in noisy case can be applied to extract the desired target signals received by array radar [15-18] for increasing the detection ability of array radar under the jamming interference environment.

For an array radar system suffering from jamming interference, the signal model mainly consists of target signals, jamming interference signal and noise [16]. In practice, the forms of transmitted radar signals are very abundant. Here assume that the transmitted radar signal, denoted by s_t , is a standard amplitude modulation (AM) signal, that is,

$$s_t(n) = B_0 [1 + k_{AM} r_m(n)] \cos(2\pi f_0 n) \quad (18)$$

where B_0 and k_{AM} are respectively the amplitude and the modulation coefficient of transmitting signal, f_0 is the carrier frequency, and $r_m(n)$ is the modulation signal. Assume that the time delay is $\Delta\tau$ and the frequency slide is Δf . So the received target signal denoted by s_e can be expressed as follows:

$$s_e(n) = B_1 [1 + k'_{AM} r_m(n)] \cos(2\pi(f_0 + \Delta f)n + \Delta\tau) \quad (19)$$

where B_1 and k'_{AM} are respectively the amplitude and the modulation coefficient of target signal received.

The received target signal s_e and transmitted radar signal s_t produced by (18) and (19) are shown in Fig. 1.

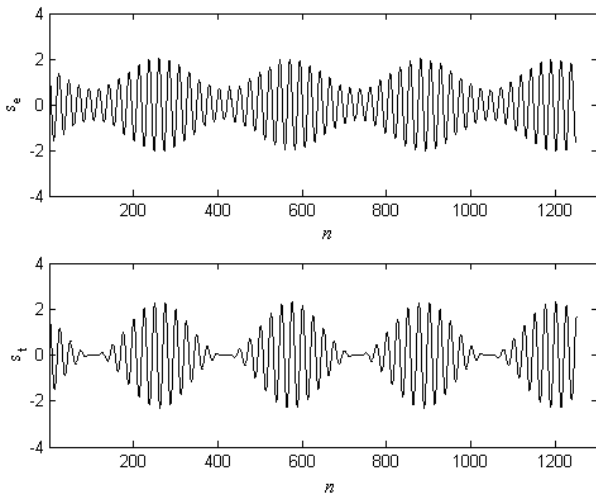


Figure 1. The received (upper) and transmitted (down) radar signals

There are also plenty of kinds of jamming interference signal forms. The noise modulation jamming interference signals [16-17] are considered in this paper. The noise modulation are further divided into noise amplitude modulation (AM), noise frequency modulation (FM) and noise AM-FM, etc. Noise FM jamming interference signals denoted by s_f were adopted here and its signal model is denoted as:

$$s_f(n) = U_0 \cos \left[2\pi f_j n + k_{FM} \sum_n u_n(n') \Delta n' \right] \quad (20)$$

where $u_n(n')$ is the modulation noise. We assume that it is Gaussian white noise with the limited band and the variance σ_f^2 . k_{FM} is the frequency modulation coefficient.

Assuming that array radar has m receiving antenna (or channels), the received radar signal can be modeled as follow:

$$\mathbf{x}'(n) = \mathbf{A}' \mathbf{s}'(n) + \mathbf{v}'(n) \quad (21)$$

where $\mathbf{x}'(n)$ is the observed signals of radar; $\mathbf{s}'(n)$ is the source signals including the received target signal, jamming interference signal and noise, etc; $\mathbf{v}'(n)$ is an unknown additive Gaussian white noise. Since \mathbf{A}' is the results that antenna responds to narrow band signal on certain direction in array radar, it is a mixture matrix.

It is easy to find that the received radar signal model in (21) is same with the BSE model in (1). Thus the extraction of the radar target signal from the signals received by array radar is a BSE problem.

IV. NUMERICAL RESULTS

A. The Benchmark Data

In this subsection, two experiments are performed to demonstrate the validity of novel algorithm. We use the benchmark data with three source signals: s_1 , s_2 and s_3 , as shown in Fig.2. They can be found in the file ABio7.mat provided by ICALAB toolbox in [1]. In our experiment, we define the signal - to - noise ratio (SNR) as follows:

$$SNR = 10 \log_{10} \left(\frac{\sigma_s^2}{\sigma^2} \right) \quad (22)$$

where σ_s^2 and σ^2 respectively denote the variance of signal and noise. In the first experiment, we fixed the SNR at 15dB, and compared our novel algorithm with the algorithm in [13]. In the second experiment, we extracted the desired signal under different SNR.

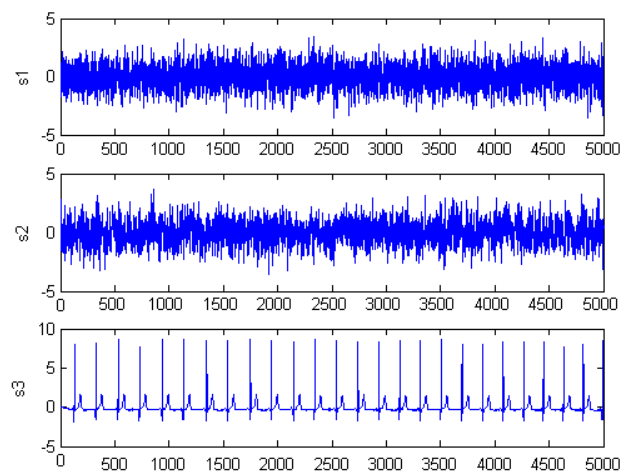


Figure 2. Three source signals in Benchmark data ($l=3$)

In the experiments, we took $p = 10$, $q = 2$, $m = 4$, $l = 3$

and calculated the AR model parameters of $s_i (i=1, 2, 3)$ using Matlab function 'aryule'. As we have one more mixture than the number of sources, this additional degree of freedom was used to estimate the variance, σ^2 , of the additive Gaussian white noise that is determined by SNR. For easily calculating the SNR and keeping good algorithm performance, we normalized \mathbf{A} into an orthonormal matrix. The performance index (PI) of desired signal $s_i (i=1, 2, 3)$ are defined to evaluate the performance of novel algorithm, that is,

$$PI(i) = 10 \log_{10} \left(\frac{1}{l-1} \left(\sum_{j=1}^l \frac{g_j^2}{g_i^2} - 1 \right) \right) \quad (23)$$

where $\mathbf{g} = \mathbf{w}^T \mathbf{A} = [g_1, g_2, g_3]^T$ is the global vector and is normalized as $\mathbf{g}^T \mathbf{g} = 1$. Generally speaking, an algorithm is evaluated to have good performing if the PI of extracted signal is below -30 dB[10].

The numerical results when SNR = 15dB in the first experiment were summarized in Table 1. The results confirmed that the MSPE algorithm extracted the signal with minimal MSPE and our algorithm extracted the signal with minimal MSCPE. Two algorithms can extract the signal based on the viewpoint for extracting a signal because all PI s for two algorithms in table 1 are below -30dB. However, the extracted signal with minimal MSCPE exactly corresponds to the desired one in the experiments, while the MSPE algorithm just did that in the third dataset. The results demonstrated that our algorithm performed better. The experiment results further verified that the desired signal has minimal MSCPE, but has not minimal MSPE.

In the second experiment, assume that s_1, s_2 and s_3 are respectively the desired signals, and the novel algorithm and AR model parameters corresponding to the desired signal are used to extract the desired signal at different SNRs. For each fixed SNR, we performed 100 different runs and averaged the value of the PI s.

The numerical results are summarized in Fig 3. We found that PI s for three desired signals are less than -30 dB when SNR is more than 15 dB from Fig. 3. When s_1 was used as the desired signal, the novel algorithm can extract this signal successfully even at SNRs = 5 dB. Two experimental results validated our algorithm.

B. The Array Radar Data

In this simulation, we assumed that the sources in (21) consisted of four kinds of signals: the received target signal s_e with AM, FM noise jamming interference signal s_f , Gaussian white noise s_n and the reference target signal s_{ee} whose carrier frequency is different from s_e . s_{ee} is set to evaluate the extraction ability of novel algorithm. Assume $p=10, m=5, l=4$. One more mixture than the number of sources was used to estimate the variance of the additive Gaussian white noise $\mathbf{v}'(n)$. It is reasonable to assume that there are more receiving sensors than sources in practice. The above four source signals and their mixture with $\mathbf{v}'(n)$ are shown in Fig. 4 and Fig. 5 respectively.

TABLE I. THE NUMERICAL RESULTS FOR BENCHMARK DATA WHEN SNR = 15 dB

Desired Signal	Signal with minimal MSPE	Signal with minimal MSCPE	Extracted Signal by MSPE	Extracted Signal by MSCPE	PI of MSPE (dB)	PI of MSCPE (dB)
s_1	s_2	s_1	s_2	s_1	-31.2	-32.1
s_2	s_1	s_2	s_1	s_2	-30.5	-30.4
s_3	s_3	s_3	s_3	s_3	-34.5	-33.4

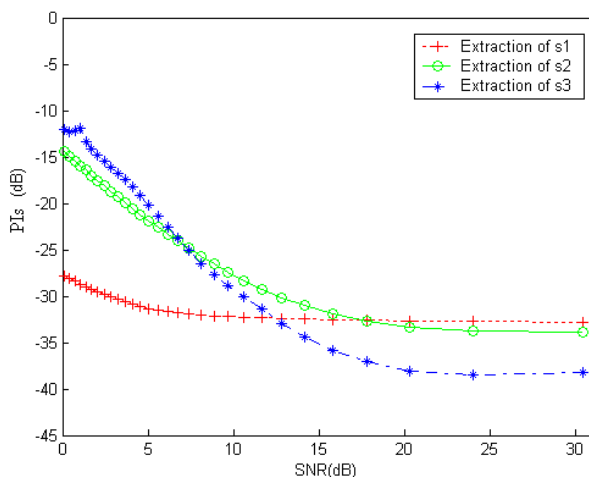


Figure 3. PIs for three desired signals at different SNRs.

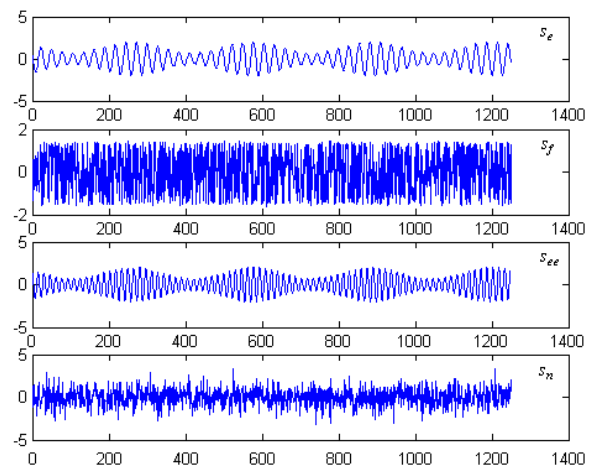


Figure 4. Four source signals received by array radar ($l=4$)

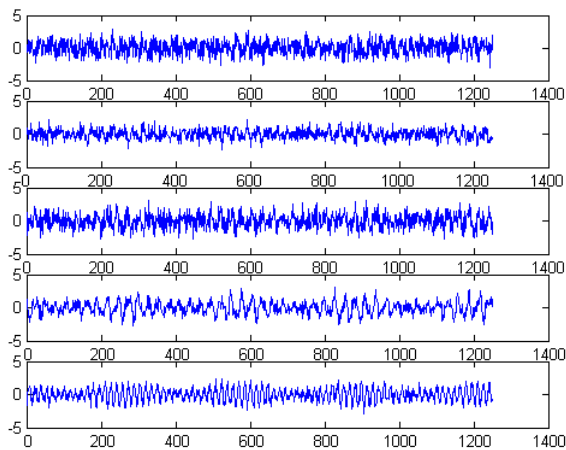


Figure 5. Mixtures of source signals with additive Gaussian white noise ($m=5$)

In this study, we extracted the received target signal s_e from the mixtures by means of AR model parameters of s_t because s_e is the echo of s_t and it is difficult to calculate the AR model parameters of s_e in practice. The performance of novel algorithm is estimated using the correlation coefficient (CC) between the extracted target signal denoted by s'_e and s_e , that is,

$$CC = \frac{\langle s_e, s'_e \rangle}{\sqrt{\langle s_e, s_e \rangle \langle s'_e, s'_e \rangle}} \quad (24)$$

where operator $\langle \cdot \rangle$ denotes the inner product, and CC is the correlation coefficient between “0” and “1”.

We executed Monte Carlo simulations under the different time delays, frequency slides and SJNRs (Signal - to - Jamming and Noise ratio, SJNR) ranging from zero to 30 dB. The results showed that the average CC exceeds 0.8 when taking SJNR > 15 dB and $q = 2$. This result illustrated that our algorithm can successfully extract the target signal under the jamming interference and noise environment. Further, we adopted the BSS method based on fast-ICA algorithm [16-17] to process the mixtures in Fig. 5. The similar results with our algorithm are obtained (Fig.6). However, our algorithm only extracted one desired signal, while BSS method separated all source signals. Thus, our algorithm has better real-time property compared with BSS method.

V. CONCLUSIONS

In this paper, a novel semi-BSE cost function based MSCPE is proposed on the viewpoint of extracting a desired signal from instantaneous noisy mixtures. Theoretical analysis and computer simulations using the benchmark data showed that the novel algorithm can extract any desired signal using its AR model parameters and embody the desired property.

The novel algorithm in noisy case was applied in the extraction of target signal received by array radar suffering from jamming interference. The numerical results confirmed that it can well extract the target signal from the received radar signals under the condition of SJNR > 15dB and $q = 2$ and has better real-time property

compared with BSS method.

Thus, this work showed that the algorithm based on MSPCE indeed works better than that based on MSPE in noisy case. The proposed algorithm has practical application prospect in array radar for increasing anti-jamming interference ability.

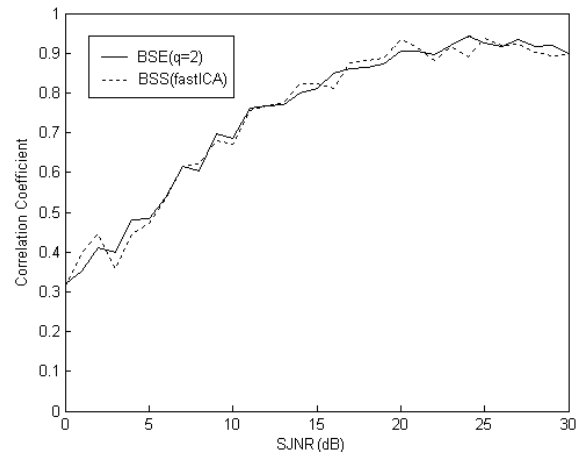


Figure 6. The performance comparisons between our algorithm and the BSS method

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