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DOA Estimation and Blind Separation of Coherent Signals

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ABSTRACT

In this paper a new blind beamforming algorithm for separating and estimating coherent signals arriving at an antenna array was proposed. This algorithm was based on Toeplitz matrix reconstruction implemented through constructing the Hermitian Toeplitz matrix. Then signal sources' direction-of-arrival(DOA) was established by spectral peak searching after using singular value decomposition of the matrix. In this way the direction vector of coherent sources used for beamforming was achieved. The new algorithm can effectively estimate the coherent signals' direction-of-arrival and separate the independent signals from different directions without knowing a priori knowledge of the signals, and the correlation coefficient of isolated signal and the source signal is close to 1. It also has a higher output SINR under the low SNR. The simulations indicated that the proposed methods worked well in a variety of situations.

Keywords: beamforming, DOA, coherent signals, blind separation, Toeplitz matrix.

INTRODUCTION

Beamforming means that forming the main lobe in the direction of the desired signal and suppressing the interferences in other directions, which is the separation of the sources, or multi-user separation actually [1]. In recent years, multi-user separation, especially blind source separation has received considerable attention in communication system because of its robust performance in unknown signal separation, which is necessary to introduce more information. Blind separation can be used to recover sources from their linear instantaneous mixtures without knowing the transcendent knowledge of the signals except for their statistical independence. Now scholars have also put forward many proposals in this area[2][3][4]. However, the separation performance of many algorithms for the coherent sources is poor.

Based on the previous researches, we know that separating the sources can be achieved with using the signal steering vector, achieved by DOA estimation. Therefore DOA estimation of the coherent sources is a key preliminary work for blind separation. Space smooth technique [5][6] is a more useful decoherence algorithm with dimension reduction currently. It has less calculation and is easy to implement, but the decoherence is at the expense of the number of array elements to the array. Due to the loss of array aperture, the number of coherent sources that can be distinguished will be reduced. A forward and backward spatial smoothing algorithm improved is proposed[7], which takes full advantage of the information of the various sub-matrix's auto-correlation and cross correlation in order to enhance the resolution of the algorithm, so that the effective aperture of the array can be reduced to the minimum. However, in the case of uniform linear array, forward and backward spatial smoothing method requires at least 2N array elements for the DOA estimation of N coherent signal sources, and performance of the algorithm is poor in the low SNR.

Consider the deficiency of above algorithms, a new DOA estimation and blind separation algorithm of coherent signals based on Toeplitz matrix reconstruction is proposed in this paper. This algorithm arranges the receive data's correlation function of each array element and reference array element (that is the first array element), to form the Hermitian Toeplitz matrix first. Then through the singular value decomposition of the matrix the signal subspace and noise subspace can be get, in this way the direction vector of coherent sources for beamforming will be achieved. The algorithm has good performance of separation with low complexity and strong ability to distinguish coherent sources.

EXPERIMENTAL SECTION

Narrow-band signals model

Consider N far-field narrow-band signals are incident on an array antenna, which the element number of is M. Assume the number of array elements is equal to the number of channels, namely the signals received by array element are transmitted from each channel to the processor, which deals with the data received from M channels.

Under the assumption above, the signals can be expressed on complex envelope as:

$$s_i(t) = u_i(t)e^{j(\omega_0 t+\varphi(t))} \quad (1)$$

$$s_i(t-\tau) = u_i(t-\tau)e^{j(\omega_0 (t-\tau)+\varphi(t-\tau))} \quad (2)$$

Where, $u_i(t)$ denotes the magnitude of the received signal, $\varphi(t)$ is the phase, and $\omega_0 = 2\pi f_0$. Assume τ is the signal delay time, thus

$$u_i(t-\tau) \approx u_i(t) \quad (3)$$

$$\varphi(t-\tau) \approx \varphi(t) \quad (4)$$

According to the above formula we have:

$$s_i(t-\tau) \approx s_i(t)e^{-j\omega_0\tau} \qquad i = 1, 2, \cdots, N \quad (5)$$

The above equation shows that for narrow-band signal $s_i(t)$, when the delay is much smaller than the reciprocal of the bandwidth, the role of delay is equivalent to the time delay of the signal's complex envelope $u_i(t)$ on the array element conversed into a phase shift, and the change of amplitude can be ignored. This conclusion is a very important role in array signal processing.

As we all know transmission environment is very complicated, and its rigorous mathematical model requires a complete description of the physical environment. However, above approach is not conducive to the algorithm. In order to get a more useful parameter model, we must simplify the wave transmission hypothesis. So we assume that:

(1) Receiving array element is in the far field, the signal can be approximately considered a plane wave.
(2) Transmission medium is lossless, linear, non-proliferation, homogeneous and isotropic.
(3) Geometry of receiving array element is much smaller than the wavelength of the incident plane wave, and the array element is no orientability, so the receiving array element can be approximately considered as an origin.
(4) The spacing of receive array element is much larger than the size of array elements, the interaction between array elements can be ignored.

Based on above assumptions, an uniform linear array is showed in Fig. 1. For a stable signal s(t), assume that the received data vector of first array element is:

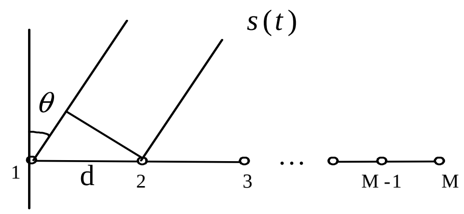


Fig. 1 Uniform linear array model

$$x_1(t) = s(t) + n_1(t) \quad (6)$$

Then the second array element receives the signal at the same time is

$$x_2(t) = x_1(t-\tau_{12}) = s(t)e^{-j\frac{2\pi}{\lambda}d\sin(\theta_i)} + n_2(t) \quad (7)$$

Where, $\tau_{12} = \frac{d\sin(\theta_i)}{c}$, the distance between adjacent array antenna is d , λ is wavelength of source signals, and θ_i is the DOA of $s_i(t)$. Similarly, the signals received by the other array elements can be also achieved, and these signals are arranged in a column vector,

$$\begin{bmatrix} x_1(t) \\ x_2(t) \\ \vdots \\ x_M(t) \end{bmatrix} = \begin{bmatrix} s(t) \\ s(t)e^{-j2\pi\frac{d}{\lambda}\sin(\theta_i)} \\ \vdots \\ s(t)e^{-j(M-1)2\pi\frac{d}{\lambda}\sin(\theta_i)} \end{bmatrix} + \begin{bmatrix} n_1(t) \\ n_2(t) \\ \vdots \\ n_M(t) \end{bmatrix} = \begin{bmatrix} 1 \\ e^{-j2\pi\frac{d}{\lambda}\sin(\theta_i)} \\ \vdots \\ e^{-j(M-1)2\pi\frac{d}{\lambda}\sin(\theta_i)} \end{bmatrix} s(t) + \begin{bmatrix} n_1(t) \\ n_2(t) \\ \vdots \\ n_M(t) \end{bmatrix} \quad (8)$$

For N signal sources, assume the incident direction respectively is $[\theta_1, \theta_2, \cdots \theta_N]$, then the above equation can be turned into :

$$\boldsymbol{X}(t) = \begin{bmatrix} 1 & 1 & \cdots & 1 \\ e^{-j2\pi\frac{d}{\lambda}\sin(\theta_1)} & e^{-j2\pi\frac{d}{\lambda}\sin(\theta_2)} & \cdots & e^{-j2\pi\frac{d}{\lambda}\sin(\theta_N)} \\ \vdots & \vdots & \ddots & \vdots \\ e^{-j(M-1)2\pi\frac{d}{\lambda}\sin(\theta_1)} & e^{-j(M-1)2\pi\frac{d}{\lambda}\sin(\theta_2)} & \cdots & e^{-j(M-1)2\pi\frac{d}{\lambda}\sin(\theta_N)} \end{bmatrix} \times \begin{bmatrix} s_1(t) \\ s_2(t) \\ \vdots \\ s_N(t) \end{bmatrix} + \begin{bmatrix} n_1(t) \\ n_2(t) \\ \vdots \\ n_M(t) \end{bmatrix} \quad (9)$$

Be expressed on matrix form as:

$$\boldsymbol{X}(t) = \boldsymbol{AS}(t) + \boldsymbol{N}(t) \quad (10)$$

Where, A is the steering vector matrix.

Coherent signals model

When considering many signals, there are three possibilities for the relationship between these signals: not relevant (ie, independent), relevant or coherent. For two stationary signals $s_i(t), s_k(t)$, their correlation coefficient can be defined as:

$$\rho_{ik} = \frac{E\left[s_i(t)s_k^*(t)\right]}{\sqrt{E\left[|s_i(t)|^2\right]E\left[|s_k(t)|^2\right]}} \quad (11)$$

By the Schwartz inequality, we know that $|\rho_{ik}| \le 1$, therefore, the correlation between signals is defined as follows:

$$\begin{cases} \rho_{ik} = 0 & s_i(t) \text{ and } s_k(t) \text{ are independent} \\ 0 < |\rho_{ik}| < 1 & s_i(t) \text{ and } s_k(t) \text{ are correlate} \\ |\rho_{ik}| = 1 & s_i(t) \text{ and } s_k(t) \text{ are coherent} \end{cases}$$

According above definition, when the signals are coherent the mathematical expression is: the difference value between the coherent signals is a complex constant, assuming that there are N coherent sources, that is,

$$s_i(t) = \alpha_i s_0(t) \quad i = 1, 2, \cdots, N \quad (12)$$

Where, $s_0(t)$ is generation source, because it generates N coherent signal sources incident on the array.
Into (10), we get the mathematical model of coherent sources:

$$\boldsymbol{X}(t) = \boldsymbol{A}\begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_N \end{bmatrix} s_0(t) + \boldsymbol{N}(t) = \boldsymbol{A\rho} s_0(t) + \boldsymbol{N}(t) \quad (13)$$

Where, ρ is $N \times 1$-dimensional vector formed by a series of complex constants.

DOA estimation based on Toeplitz matrix reconstruction

In this section, the general condition is given. Suppose that there are M antenna in a uniform linear array(ULA) and N unknown sources, its structure and received data vector are shown in Fig. 2, then the received signals of each array element respectively is $x_0(t), x_1(t), \cdots x_{M-1}(t)$. The noise is Gaussian white noise, which the power of is σ^2, and noise and signals are independent, So the kth received signal is shown as follow[10]:

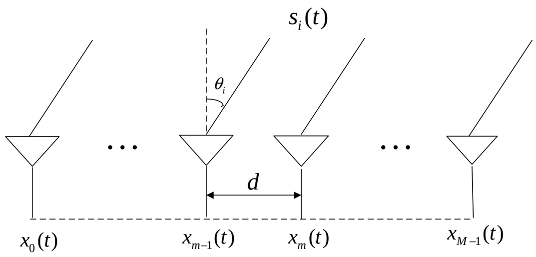


Fig. 2 Approved Linear Array Model

$$x_k(t) = \sum_{i=1}^{N} s_i(t) e^{-j\frac{2\pi}{\lambda} dk \sin(\theta_i)} + n_k(t) = \boldsymbol{A}(k)[s_1(t), s_2(t), \cdots, s_N(t)]^T + n_k(t) \quad (14)$$

Where $s_i(t)$ denotes the ith signal source, $n_k(t)$ denotes white Gaussian noise on the kth array element. $e^{-j\frac{2\pi}{\lambda} dk \sin(\theta_i)}$ denotes the kth line and the ith column of data of steering vector matrix A,

$$\boldsymbol{A} = [a(\theta_1), a(\theta_2), \cdots, a(\theta_N)] \quad (15)$$

Where $\boldsymbol{a}(\theta_i) = [1, e^{-j\frac{2\pi d}{\lambda}\sin\theta_i}, \cdots, e^{-j(M-1)\frac{2\pi d}{\lambda}\sin\theta_i}]^T$ stands for the steering vector on θ_i of $s_i(t)$. $\boldsymbol{A}(k)$ $(k = 1, 2, \cdots, M)$ in (14) denotes all the elements of steering vectors A in the kth line.
Autocorrelation matrix of received signals is defined as [3]:

$$\boldsymbol{R} = E[\boldsymbol{XX}^H] = \boldsymbol{APA}^H + \sigma^2 \boldsymbol{I} \quad (16)$$

Where, $\boldsymbol{P} = E[\boldsymbol{SS}^H]$ is autocorrelation matrix of source signals, σ^2 is the power of noise. Superscript T and H expresses respectively transposition and conjugate transposition.
Do eigen-decomposition: $\boldsymbol{R} = \boldsymbol{U\Sigma U}^H$ (17)

Where, $\boldsymbol{U}$ is eigenvector matrix, diagonal matrix $\boldsymbol{\Sigma}$ which formed by the eigenvalues is:

$$\boldsymbol{\Sigma} = \begin{bmatrix} \lambda_1 & & & \\ & \lambda_2 & & \\ & & \ddots & \\ & & & \lambda_M \end{bmatrix} \tag{18}$$

And the eigenvalues satisfy the following relationship:

$$\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_N > \lambda_{N+1} = \cdots = \lambda_M = \sigma^2 \tag{19}$$

Two diagonal matrices are defined as follows:

$$\boldsymbol{\Sigma_S} = \begin{bmatrix} \lambda_1 & & & \\ & \lambda_2 & & \\ & & \ddots & \\ & & & \lambda_N \end{bmatrix}, \quad \boldsymbol{\Sigma_N} = \begin{bmatrix} \lambda_{N+1} & & & \\ & \lambda_{N+2} & & \\ & & \ddots & \\ & & & \lambda_M \end{bmatrix} \tag{20}$$

Where, $\boldsymbol{\Sigma_S}$ is diagonal matrix formed by large eigenvalues, $\boldsymbol{\Sigma_N}$ is diagonal matrix formed by small eigenvalues. Then the eigenvector matrix corresponding to eigenvalues is divided into two parts: one is signal subspace $\boldsymbol{U_S} = [e_1, e_2, \cdots, e_N]$ with large eigenvalues, the other is noise subspace $\boldsymbol{U}_N = [e_{N+1}, e_{N+1}, \cdots e_M]$ with small eigenvalues. Thus (17) can be expressed as:

$$\boldsymbol{R} = \sum_{i=1}^{N} \lambda_i e_i e_i^{\ H} + \sum_{j=N+1}^{M} \lambda_j e_j e_j^{\ H} = [\boldsymbol{U}_S, \boldsymbol{U}_N]\boldsymbol{\Sigma}[\boldsymbol{U}_S, \boldsymbol{U}_N]^H = \boldsymbol{U}_S \boldsymbol{\Sigma}_S \boldsymbol{U}_S^{\ H} + \sigma^2 \boldsymbol{U}_N \boldsymbol{U}_N^{\ H} \tag{21}$$

For the ideal case of independent signal source, the array covariance matrix R has the Toeplitz structure. But in reality, due to finite snapshots and system deviation, and the presence of coherent sources, the Toeplitz property of covariance matrix R is damaged, generally matrix is diagonally dominant, which thus affects the performance of DOA based on covariance matrix decomposition. In this paper, a new Toeplitz matrix is reconstructed from correlation function, which is extracted by the received data of each array element, in order to achieve the purpose of decoherence.
We can get the received data vector of the first array element through (14):

$$x_1(t) = \sum_{i=1}^{N} s_i(t) + n_1(t) = \boldsymbol{A}(1)\boldsymbol{S}^T + n_1(t) \tag{22}$$

Correlation function is defined as follows:

$$r(k-1) = E[x_1 x_k^H] = \boldsymbol{A}(1)E[\boldsymbol{SS}^H]\boldsymbol{A}^H(k) + \sigma^2 \boldsymbol{I} = \boldsymbol{A}(1)\boldsymbol{R}_s \boldsymbol{A}^H(k) + \sigma^2 \boldsymbol{I} \tag{23}$$

Where, $\boldsymbol{R}_s$ is autocovariance matrix of signal sources, $\boldsymbol{S} = [s_1, s_2, \cdots, s_N]^T$. When k changes from 1 to M, the correlation vector received is $[r(0), r(1), \cdots, r(M-1)]$, and

$$[r(0), r(1), \cdots, r(M-1)] = \boldsymbol{A}(1)\boldsymbol{R}_s[A^H(1), A^H(2), \cdots, A^H(M)] \tag{24}$$

It is obvious that the data vector contains all the information of sources. The matrix formed by M correlation functions as:

$$\boldsymbol{R}_T = \begin{bmatrix} r(0) & r(1) & \cdots & r(M-1) \\ r(-1) & r(0) & \cdots & r(M-2) \\ \vdots & \vdots & \cdots & \vdots \\ r(-M+1) & r(-M+2) & \cdots & r(0) \end{bmatrix}_{M \times M} \tag{25}$$

and $r(-k) = r^*(k)$. It can be proved that $\boldsymbol{R}_T$ is $M\times M$ Hermitian Toeplitz matrix. With the singular value decomposition (SVD) of $\boldsymbol{R}_T$, signal subspace $\boldsymbol{U}_S$ and noise subspace $\boldsymbol{U}_N$ can be obtained. Then the sources' DOA can be established by spectral peak searching. The spectrum estimation formula is:

$$P_{MUSIC} = \frac{1}{\boldsymbol{a}^H(\theta)\boldsymbol{U}_N\boldsymbol{U}_N^H\boldsymbol{a}(\theta)} \quad (26)$$

The angle corresponding to the maximum points in spectral peaks is at the incidence direction of signal.

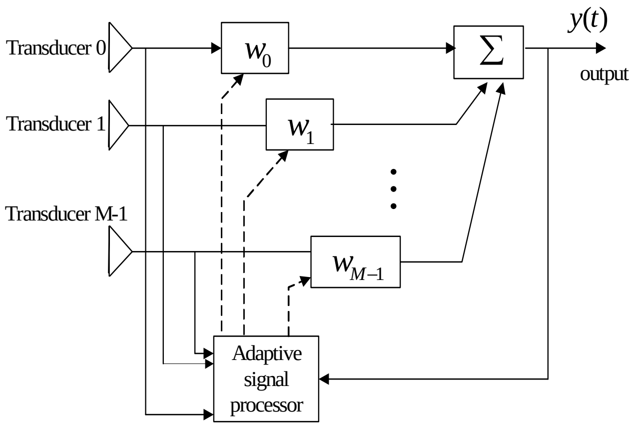


Fig. 3 Beamformer system

Beamforming and blind separation

The physical meaning of beamforming is that although array antenna pattern is omnidirectional, but the direction gain of received array can be adjust to the desired direction after the weight sum of the output of the array, equivalent to the formation of a beam. As shown in Fig. 3, the basic idea is to complete the "orientation" by adjusting the weighting coefficients.

Where， $\boldsymbol{w} = [w_0, w_1, \cdots, w_{M-1}]^H$ ， thus the output is:

$$y(t) = \boldsymbol{w}^H \boldsymbol{x}(t) = \sum_{m=0}^{M-1} w_m^* x_m(t) \quad (27)$$

In this paper, the multiple-input multiple-output system by the composition of N-beamformers is shown in Fig. 4. According to the basic concept of the beamformer, the output of each beamformer is:

$$\boldsymbol{Y}_i = \boldsymbol{w}_i^H \boldsymbol{X} \text{ ， (i.e. } i = 1,\ldots,N\text{)} \quad (28)$$

Where $\boldsymbol{w}_i$ denotes the ith complex weight vector of beamformer.

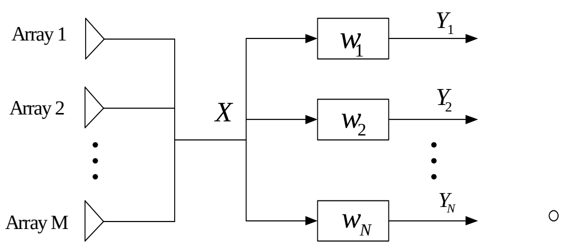


Fig. 4 Multi-user beamformer system

Now the question is, how to make each beamformer output to lock a signal source by adjusting all of the weight vector w under an optimal rule, in the condition of without knowing the steering vector and the transcendent knowledge of the signals.

Based on the estimated steering vector of each source vector, then beamforming is achieved, which separates the individual user signals. The minimum output energy (MOE) criterion which has important applications in communications and radar signal processing is used in beamforming to design the weight vector $\boldsymbol{w}_i$, the sampled signals are expressed as discrete form, considering the average of the output energy by L snapshot being minimum, namely:

$$\min_{\boldsymbol{w}} \frac{1}{L}\sum_{t=1}^{L} | y(t) |^2 = \min_{\boldsymbol{w}} \frac{1}{L}\sum_{t=1}^{L} | \boldsymbol{w}^H \boldsymbol{X}(t) |^2 \quad (29)$$

The autocorrelation matrix of signal vector $\boldsymbol{X}(t)$ is:

$$\hat{\boldsymbol{R}}_{xx} = \frac{1}{L}\sum_{t=1}^{L} \boldsymbol{X}(t)\boldsymbol{X}^H(t) \quad (30)$$

Then MOE criteria corresponding to (28) can be transformed to:

$$\min_{\boldsymbol{w}} \frac{1}{L}\sum_{t=1}^{L} | y(t) |^2 = \min_{\boldsymbol{w}} \boldsymbol{w}^H \left(\frac{1}{L}\sum_{t=1}^{L} \boldsymbol{X}(t)\boldsymbol{X}^H(t)\right)\boldsymbol{w} = \min_{\boldsymbol{w}} \boldsymbol{w}^H \hat{\boldsymbol{R}}_{xx}\boldsymbol{w} \quad (31)$$

When $N \to \infty$,

$$E\{| y(t) |^2\} = \lim_{L\to\infty} \frac{1}{L}\sum_{t=1}^{L} | y(t) |^2 = \boldsymbol{w}^H \boldsymbol{R}_{xx}\boldsymbol{w} \quad (32)$$

Equation (10) is discretized and then into above equation:

$$E\{| y(t) |^2\} = E\{| s_d(t) |^2\} | \boldsymbol{w}^H \boldsymbol{a}(\theta_d) |^2 + \sum_{i=1}^{J} E\{| s_i(t) |^2\} | \boldsymbol{w}^H \boldsymbol{a}(\theta_i) |^2 + \sigma^2 | \boldsymbol{w} |^2 \quad (32)$$

Seen from above equation, the first is the desired signal, interference signals is the second and the third term is additive noise. The weight vector $\boldsymbol{w}$ satisfies the constraints:

$$\boldsymbol{w}^H \boldsymbol{a}(\theta_d) = \boldsymbol{a}^H(\theta_d)\boldsymbol{w} = 1 \text{ (beamforming)} \quad (34)$$

$$\boldsymbol{w}^H \boldsymbol{a}(\theta_i) = 0, (i = 1, \cdots, J) \text{ (null form)} \quad (35)$$

The beamformer will only achieve the desired signal, while reject all other interference signals. Therefore, the best design of beamformer becomes making the output energy $E\left\{|y(t)|^2\right\}$ minimized under the above constraints.

Solve the optimization problem with Largange algorithm. Then objective function $J(\boldsymbol{w})$ can be constructed according to (32) and (34):

$$J(\boldsymbol{w}) = \boldsymbol{w}^H \boldsymbol{R}_{xx}\boldsymbol{w} + \lambda[1 - \boldsymbol{w}^H \boldsymbol{a}(\theta_d)] \quad (36)$$

When $\partial J(\boldsymbol{w}) / \partial \boldsymbol{w} = 0$, thus:

$$\boldsymbol{w}_{opt} = \lambda \boldsymbol{R}_{xx}^{-1}\boldsymbol{a}(\theta_d) \quad (37)$$

Insert $\boldsymbol{w}_{opt}$ to the constraint (34), λ can be obtained,

$$\lambda = \frac{1}{\boldsymbol{a}^H(\theta_d)\boldsymbol{R}_{xx}^{-1}\boldsymbol{a}(\theta_d)} \quad (38)$$

λ is inserted into (37), eventually the beamformer get from output energy minimization is

$$\boldsymbol{w}_{opt} = \frac{\boldsymbol{R}_{xx}^{-1}\boldsymbol{a}(\theta_d)}{\boldsymbol{a}^H(\theta_d)\boldsymbol{R}_{xx}^{-1}\boldsymbol{a}(\theta_d)} \quad (39)$$

Consider the Toeplitz property of covariance matrix R for coherent signals will be damaged, the matrix needs to be reconstructed in order to achieve the purpose of decoherence. Autocovariance matrix after reconstruction is $\boldsymbol{R}_T$, steering vector $\hat{\boldsymbol{a}}(\theta_i)$ of the source can be obtained from above DOA estimation, so the optimal weight beamformer optimal weight is:

$$\boldsymbol{w}_i = \frac{\boldsymbol{R}_T^{-1}\hat{\boldsymbol{a}}(\theta_i)}{\hat{\boldsymbol{a}}^H(\theta_i)\boldsymbol{R}_T^{-1}\hat{\boldsymbol{a}}(\theta_i)} \tag{40}$$

Algorithm Summary

Based on above analysis, the process is expressed as follows:

1. Generate the received data of the first array element according to (22).
2. Build correlation function $r(k-1), k = 1,...,M$.
3. Form Hermitian Toeplitz matrix $\boldsymbol{R}_T$ through (25).
4. Establish signal subspace $\boldsymbol{U}_S$ by singular value decomposition of $\boldsymbol{R}_T$.
5. Estimate coherent signals' DOA by spectral peak searching.
6. Obtain the optimal beamforming weight vector $\boldsymbol{w}_i$ through (40).

In addition, for the performance evaluation of blind source separation algorithm, we take the correlation coefficient of the separated signal y_i and the corresponding source signal s_j as a measure [12]:

$$\rho_{ij} = \sqrt{\frac{|E(y_i^* s_j)|^2}{E(|y_i|^2)E(|s_j|^2)}} \tag{41}$$

If $\rho_{ij} = 1$, indicating that the ith separated signal and the jth source signal are identical. Thus the estimation error is inevitable, ρ_{ij} can only be close to 1, and the more the value approaches to 1, the better the separation performance is.

RESULTS AND DISCUSSION

Consider a linear array of eight elements exposed to some coherent sources. The spacing between adjacent array antenna is half the wave length. The noise is additive white Gaussian noise, which power is 1.

DOA estimation of coherent sources

Consider four coherent sources arriving from $-50^\circ, -30^\circ, 10^\circ, 40^\circ$, the corresponding fading factor margin is $1, 0.9, 0.8, 0.7$, signal to noise ratio are 20dB, 512 snapshots, and 100 times Monte-Carlo experiment. As shown in Fig. 5, the spatial spectrum of reconstruction algorithm based on Toeplitz matrix forms a more sharp peak in the direction of the source, and can accurate DOA of coherent sources more accurately.

DOA estimation deviation as SNR changes

Three coherent sources arriving from $-40^\circ, 10^\circ, 20^\circ$, the corresponding fading factor margin is $1, 0.9, 0.8$, signal to noise ratio changes form 0dB to 20dB, we calculate it every 1dB, and 100 times Monte-Carlo experiment. The result of simulation is showed in Fig. 6. It can be seen from Fig. 6, under the circumstances with different signal to noise ratio, the proposed reconstruction algorithm based on Toeplitz matrix maintains a smaller estimation deviation.

Testing separation performance of each source

Consider three coherent sources arriving from -30°, 15°, 30°, the corresponding fading factor margin is $1, 0.9, 0.8$, signal to noise ratio are 20dB, 512 snapshots. Fig. 7 is array pattern corresponding to three output ports. From the figure, we see the algorithm can separate each source, and obtain a greater gain in the direction of useful source, thus has a deep nulling in the direction of the other sources. And the correlation coefficients of every isolated signal and responding source signal are 0.991、0.989、0.996, which means the performance of separation is good.

Relationship of output SNR and signal angle

Assuse three coherent sources, the angle between signals changes form 5° to 40°, we calculate it every 5°. The result of simulation is showed in Fig. 8. From the figure, we can see that the algorithm is stable, and has a strong output signal to noise ratio.

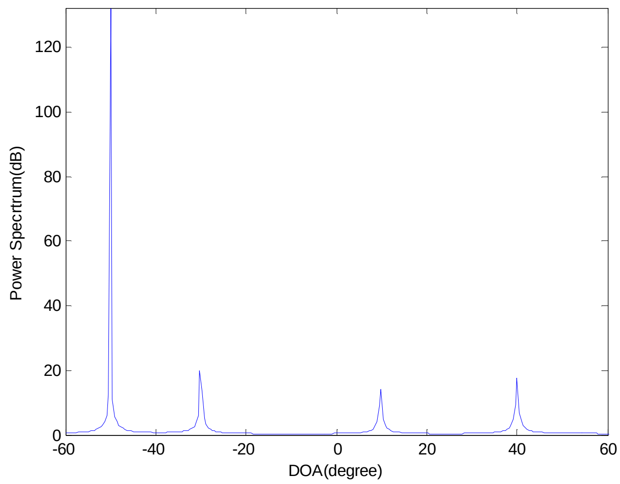


Fig. 5 DOA estimation of coherent signal sources

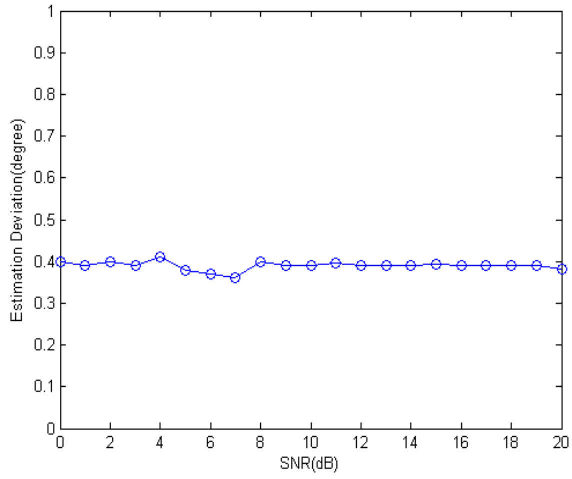
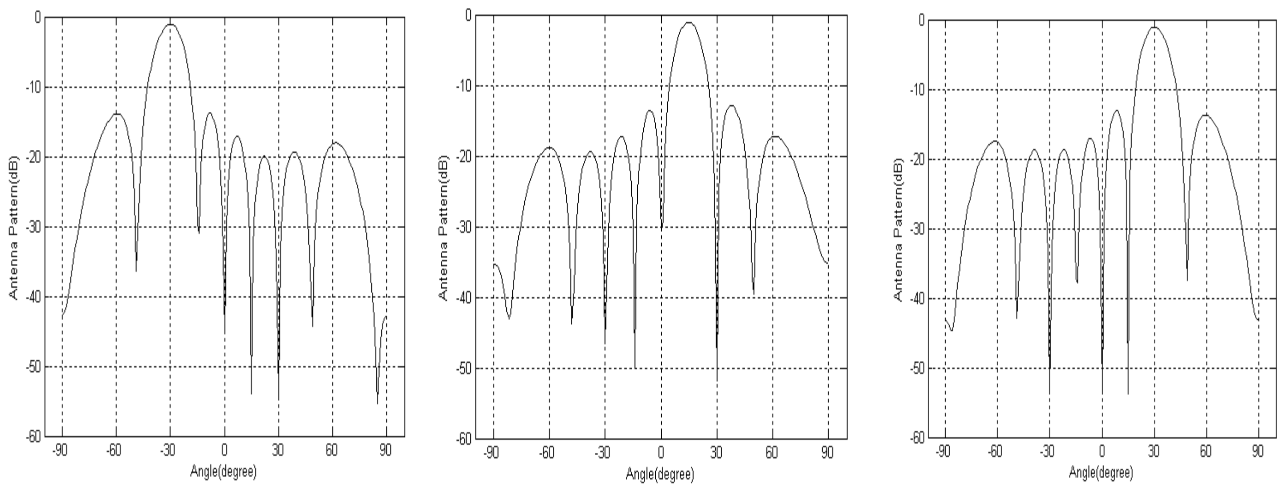


Fig. 6 DOA estimation deviation with SNR

Relationship ofinput SNR and output SINR

Consider three coherent sources arriving from $-30^{\circ}, 15^{\circ}, 30^{\circ}$, the corresponding fading factor margin is $1, 0.9, 0.8$, 512 snapshots. It can be seen from Fig. 9, when the input SNR increases, the average of output SINR is also growing, which means the better stable performance of the algorithm. The output of each beamformer can capture a user signal, suppress remaining signal as interference signal. And the algorithm also has a higher output SINR in the case of low input SNR.



(a) source 1 (-30°) (b) source 2 (15) (c) source 3 (30)

Fig. 7 Array pattern of each source

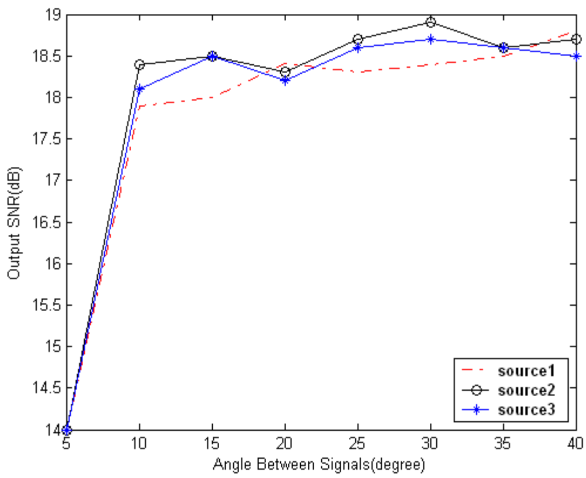


Fig. 8 Relation of output SNR and signal degree

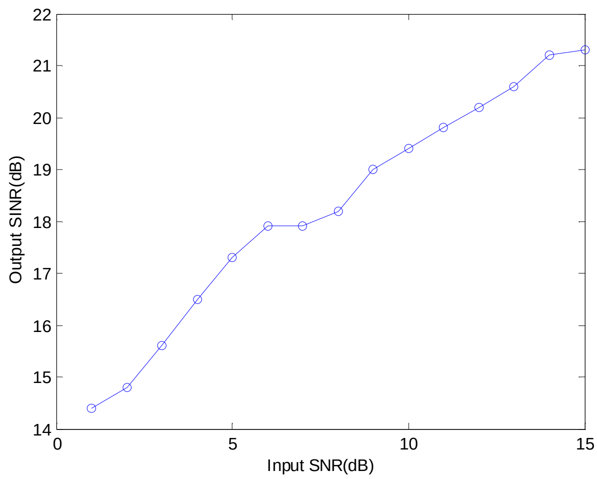


Fig. 9 Relation of input SNR and output SINR

CONCLUSION

On the research of DOA estimation and blind separation algorithms of coherent sources, a new separation algorithm based on Toeplitz matrix reconstruction is proposed in this paper, through arranging the receive data's correlation function of each array element and reference array element to form the Hermitian Toeplitz matrix for decoherence, then steering vector of coherent sources can be achieved by spectral peak searching in the purpose of beamforming. The algorithm can estimate signals' DOA quickly and capture the desired weight vector, so it has a good blind separation to coherent sources. The simulation results indicates the effectiveness and robustness of the propose dalgorithm.

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