Coprime array-based robust beamforming using covariance matrix reconstruction technique

Ke Liu\textsuperscript{1,2*} and Yimin D. Zhang\textsuperscript{2}

\textsuperscript{1} College of Automation, Harbin Engineering University, Harbin 150001, China
\textsuperscript{2} Department of Electrical and Computer Engineering, Temple University, Philadelphia, PA 19122, USA
* E-mail: liuke_heu@163.com

Abstract: A novel robust adaptive beamforming algorithm based on coprime array is proposed in this paper. First, we exploit the virtual array structure of coprime coarray to construct two subspaces. The first subspace is obtained from the covariance matrix of the virtual uniform linear array, whereas the second one is obtained by integrating spatial spectrum over each angular sector of signal. Then, by using a closed-form expression of projection-based approach, the steering vectors of signals are estimated from the intersection of the two subspaces. Moreover, according to the covariance fitting theory, the power associated with the desired signal, interference signals and noise is obtained from the virtual sample covariance matrix. In addition, to reconstruct the interference-plus-noise covariance matrix (INCM), the maximum correlation principle is used to transfer the virtual SVs of signals to real ones corresponding to a physical array. Finally, with the estimated the SV of the desired signal and the INCM, the proposed robust algorithm is devised. Simulation results demonstrate the superiority and effectiveness of the proposed algorithm.

1 Introduction

To enhance the directional gain of the desired signal (DS) and suppress interference signals, adaptive beamforming approaches are widely applied in various applications [1]-[3], such as wireless communications, radar, radio astronomy and medical imaging. Provided that the steering vector (SV) of the DS and the covariance matrix are accurately known, the traditional minimum variance distortionless response (MVDR) beamer [4] achieves excellent performance. However, when the assumed DS direction has a mismatch or the covariance matrix contains the desired signal component, the MVDR beamer may cause severe performance degradation. To overcome this shortcoming, a number of approaches have been developed to improve the robustness of beamformer in the past several decades. These approaches can be divided into the following two major categories: non-reconstruction approaches and reconstruction approaches. The former directly processes the sample covariance matrix (SCM) without a reconstruction operation. Such approaches include worst-case performance optimization [5], SV-estimation-based approach [6], [7], and diagonal loading [8], [9]. However, these methods cannot achieve near-optimal performance due to the self-nulling issue of the DS as a result of utilizing the sample covariance matrix.

As its name implies, reconstruction approaches [10]-[12] contain a key step of the SCM reconstruction corresponding to the interference signals. Compared with the non-reconstruction approaches, the reconstruction approaches generally yield an improved performance, which can be explained as follows. Recalling that the weight vector of the adaptive MVDR beamer is a function of the INCM and the SV of the DS. By removing the DS component from the SCM, the self-nulling phenomenon of the DS is avoided. On the other hand, to avoid the look direction mismatch of the DS, the SV of the DS is accurately estimated by using certain optimization method. Hence, the output signal-to-interference-plus-noise ratio (SINR) of the reconstruction-based algorithms can closely converge to the optimal solution. It is noted that, in the reconstruction-based approaches, the noise power, the SV and the power of the each interference signal affect the INCM reconstruction. As a result, for INCM-reconstruction-based methods, it becomes critical to guarantee the estimation accuracy of the SVs and the power of the interference signals. Toward this end, subspace-based methods are attractive due to their simplicity and high efficiency. In [13], the DS SV and the INCM are estimated by subspace-based methods. However, the beamformer performance still tremendously degrades in presence of look direction errors of the DS. In [14] [15], the maximum correlation principle is used to reconstruct the INCM, but the performance degrades when the input SNR is closed to the input interference-noise ratio (INR). The approach in [16] makes use of the a priori information about the angular sections of the signals and combines projection methods to obtain a more precise estimation of the INCM , but it has performance degradation with the increase of the interferer numbers.

Recently, the coprime-array-based signal processing approaches [17]-[28] attract a great attention since they can yield a higher estimated accuracy and a stronger interference suppression capability than the uniform linear array (ULA) counterpart when the same number of sensors are used. The main concept of the coprime array configuration is to use a pair of coprime sparse subarrays to compose a non-uniform linear array. By exploiting the difference coarray property of coprime coarray, a virtual ULA with more sensors than the number of physical ones is formulated. The equivalent received signals based on the virtual array are then utilized for parameter estimation. Compared to coprime-array-based DOA estimation, which has attracted considerable interests, adaptive beamforming techniques based on coprime array are much less studied. Among the few references published in this area, reference [24] introduced a compressive matrix to transfer the SV of a virtual array to that of a physical array, based on which a coprime-array-based adaptive beamforming approach is developed. Such approach suffers from performance loss because of the reduced number of virtual sensors as a result of sparse sampling. In [25], based on the spatial spectrum estimated using a virtual array, the source directions and interference power are sequentially estimated and a coprime array adaptive beamformer is then constructed. In this case, the interference power obtained from Capon spectrum estimation may not be accurate, thus compromising the accuracy of the reconstructed interference covariance matrix and, subsequently, the adaptive beamformer. In references [26] and [27], a coprime array consisting of a pair of physical uniform linear subarrays is considered, and the signal vectors received in these subarrays are separately processed to estimate
the DOA and power of the signals. Note that, in this approach, the number of sources that can be estimated is limited by that of the physical sensors in each uniform linear subarray. In reference [28], a sparse-reconstruction-based source estimation algorithm is proposed to simultaneously estimate the DOA and power of the signals. Such approach can be directly extended to adaptive beamforming. It is noted that, however, it could encounter the off-grid issue and thus compromise the estimation performance.

Motivated by the above fact, in this paper, we propose a novel subspace approach to reconstruct INCM using a coprime array. An accurate estimation associated with the SVs and the power of signals is first obtained by utilizing virtual aperture of the coprime array. Based on the vector correlation property, a connection can be built between the physical coprime array and the virtual ULA. We then obtain a high-accuracy estimation of the physical array-based INCM and the DS SV and, based on which, a novel robust adaptive beamformer is formulated. Simulation results demonstrate that the proposed coprime array adaptive beamforming algorithm is superior to existing approaches in terms of the output SINR.

The key contribution of the proposed work lies in the accurate estimation of the INCM and the DS SV that leads to superior beamforming performance. This is made possible by utilizing the virtual array of the coprime array which offers a larger aperture and a higher number of degrees of freedom. We use a novel approach to estimate the signal SVs and the interference power based on the virtual array. The signal SVs corresponding to the virtual array are then mapped to reconstruct the INCM in the physical coprime array based on the vector correlation property.

The rest of the paper is organized as follows. Section 2 introduces the array model based on coprime coarray. The proposed robust adaptive beamforming algorithm is presented in Section 3. In Section 4, simulation results are provided to illustrate the effectiveness of the proposed algorithm. Finally, conclusions are given in Section 5.

Notations: We use upper-case and lower-case to denote vector and matrices, respectively. In particular, $1_M$ denotes the $M \times M$ identity matrix. The superscripts $(\cdot)^T$ and $(\cdot)^H$ respectively imply transpose and conjugate transpose of a matrix or vector, and $(\cdot)^{-1}$ denotes matrix inversion operator. $\text{diag}(\cdot)$ and $\text{vec}(\cdot)$ represent diagonalization and vectorization operator, respectively. $\otimes$ denotes the Kronecker product, and $E(\cdot)$ denotes the statistical expectation operator. $|\cdot|$ and $\|\cdot\|$ denote absolute value and Frobenius norm, respectively.

2 Signal model

Without loss of generality, we assume that $M$ and $N$ are a pair of coprime integers with $M < N$. Consider two uniform linear subarrays with sparse space and denote the unit inter-element spacing $d$ to be half wavelength $\lambda/2$. For the first subarray, there are $M$ sensors with inter-element spacing $Nd$, while the second subarray has $N$ sensors with inter-element spacing $Md$. Assume that the first sensor of both subarrays shares the same position and is set as the reference. There are $Q$ far-field uncorrelated narrowband signals impinging on the coprime array from directions $\{\theta_1, \theta_2, \ldots, \theta_Q\}$.

The first signal is considered as the DS. The received signal vector $x(k) \in \mathbb{C}^{M \times N \times 1}$ is written as

$$x(k) = \sum_{q=1}^{Q} a(\theta_q) s_q(k) + n(k) = A_1 s_q(k) + n(k),$$

where $k$ is the snapshot index, $a(\theta_q) = [1, e^{j2\pi k \sin(\theta_q)}]$, $e^{j2\pi k \frac{N}{M} \sin(\theta_q)}$ is the SV of signal $s_q$, $p_c \in \{Mnd \leq n \leq M - 1\} \cup \{Nmd \leq m \leq M - 1\}$ denotes the position of the $c$th physical array sensor. In addition, $A = [a(\theta_1), a(\theta_2), \ldots, a(\theta_Q)]$ is the steering matrix, and $n(k)$ is the noise vector whose elements are assumed to be independent and identically distributed complex Gaussian random variables.

The output of the adaptive beamformer is expressed as

$$y(k) = w^H x(k),$$

where $w \in \mathbb{C}^{(M+N-1) \times 1}$ is the weight vector of the beamformer and is obtained by solving the following optimization problem

$$\min_w w^H R_{in} w \quad \text{subject to} \quad w^H a(\theta_1) = 1,$$

which is the well-known MVDR beamformer [4].

In practice, $R_{in}$ is difficult to directly obtain and thus is usually replaced by the SCM

$$R = \frac{1}{L} \sum_{k=1}^{L} x(k)x^H(k)$$

from $L$ snapshots. When the SCM is used in computing the beamformer weights, the SINR performance is not closely optimal. That is due to the fact that SCM contains the DS component which leads to the self-nulling phenomenon of DS. The interference-plus-noise covariance matrix reconstruction approach can be used to solve this issue efficiently.

3 Proposed algorithm

In order to implement the optimal closed-form solution of the MVDR beamformer depicted in (5), we need to obtain the INCM and the SV of the DS. The reconstruction of the INCM requires the SVs and the power of all interference signals as well as the noise power. Therefore, in total, we need three pieces of information, i.e., the SVs of all signals (including that of the DS and of the interference signals), the power of interference signals, and the noise power.

In this paper, we develop a robust beamformer algorithm based on the high-accuracy estimation of these parameters. By utilizing a coprime array structure that offers a large virtual array aperture with the same number of physical sensors. First, we use the projection-based method in the context of coprime array to estimate the SVs of all signals. Then, by using the covariance fitting method, the power of the interference signals and noise is obtained. It is noted that the estimated SVs of all signals are based on the virtual array. The above estimated information is then used to reconstruct the INCM and the DS SV corresponding to the physical sensor array through the utilization of the maximum correlation principle. After obtaining the INCM and the DS SV associated with the physical array elements, the weight vector of the proposed adaptive beamformer is computed according to (5).

3.1 Coprime array-based steering vector estimation

To take the advantage of the virtual array aperture of a coprime coarray to obtain a high-precision estimation for the signal SV, we first vectorize the SCM $R$ as

$$z = \text{vec}(R) = \tilde{A} b + \sigma_n^2 \tilde{I},$$

where $\tilde{A} = [\tilde{a}(\theta_1), \tilde{a}(\theta_2), \ldots, \tilde{a}(\theta_Q)]$, $\tilde{a}(\theta_q) = a^*(\theta_q) \otimes a(\theta_q)$, $b = [\sigma_1^2, \sigma_2^2, \ldots, \sigma_Q^2]$, and $\tilde{I} = \text{vec}(I_{M+N-1})$. It is easy to find that the rank of the single-sample covariance matrix $R_{zz} = zz^H$ is one.
Considering the spatial domain property, we construct the following matrix

\[ C_j = \int_{\Theta_{j}} c(\theta) \tilde{a}(\theta) a^H(\theta) d\theta, \]  

(14)

where \( c(\theta) \) is the probability density function and could be set to either 1 [6] or \( 1/|\hat{a}(\theta) R^{-1} \hat{a}(\theta)'| [11] \), and \( \Theta_j, j = 1, 2, \ldots, Q \), denotes the angular sectors where the \( j \)th signal is located. Then, \( C_j \) is eigendecomposed as

\[ C_j = \sum_{i=q}^{M+1} \beta_q v_q v_q^H = V_q \Psi_q V_q^H + V_n \Psi_n V_n^H, \]  

(15)

where \( \beta_q, q = 1, 2, \ldots, M+1 \), are the eigenvalues of \( C_j \) in the descending order, and \( v_q \) is the eigenvector corresponding to \( \beta_q \). Similar to (10), \( V_n \) contains \( H \) dominant eigenvector associated with the \( H \) largest eigenvalues, while \( V_n \) contains the remaining \( M+1-H \) eigenvectors. Following the method in [15], \( H \) is set as the minimum integer that satisfies \( \sum_{q=1}^{H} \beta_q \geq \beta_q > g \), where \( g \in (0,1) \) is a pre-determined parameter. Therefore, \( \tilde{a}_j \) lies in the subspace spanned by the columns of \( V_n \), i.e.,

\[ \tilde{a}_j \in \Xi_n = \{ \tilde{a} : \tilde{a} = V_n \tilde{a}_n \}. \]  

(16)

where \( \tilde{a}_n \) is a coefficient vector similar to \( a_n \).

To sum up, the SV of the \( j \)th signal \( \tilde{a}_j \) lies in the intersection of \( \Xi_\Sigma \) and \( \Xi_n \), i.e., \( \tilde{a}_j \in \Xi_\Sigma \cap \Xi_n \). When using the iterative projection approach to obtain \( \tilde{a}_j \), the iteration equation is expressed as

\[ \tilde{a}_{j,h+1} = \bar{P}_1 \bar{P}_2 \tilde{a}_{j,h}, \]  

(17)

where the iterative start point is the assumed SV of \( \tilde{a}_j \), \( h \) is the iteration index, \( \bar{P}_1 = P_o P_o^H \), and \( \bar{P}_2 = V_n V_n^H \). When \( h \to \infty \), \( \tilde{a}_{j,h} \) will converge to the actual SV of the \( j \)th signal [13] [15] [16]. By using the results in [31], we can prove that the maximum eigenvalue of \( \bar{P}_1 \bar{P}_2 \) is unity, i.e.,

\[ \text{eig}_{\text{max}}(\bar{P}_1 \bar{P}_2) = \max_{u^H u = 1} u^H \bar{P}_1 \bar{P}_2 u = \text{eig}_{\text{max}}(\bar{P}_1) = 1, \]  

(18)

where \( \text{eig}_{\text{max}}(\cdot) \) denotes the maximum eigenvalue of a matrix. Therefore, considering the norm constraint, the SV of the \( j \)th signal \( \tilde{a}_j \) is obtained as

\[ \tilde{a}_j = \sqrt{\sum_{n=1}^{N} \Gamma(P_1 P_2), \quad j = 1, 2, \ldots, Q, \]  

(19)

where \( \Gamma[P_1 P_2] \) denotes the eigenvector corresponding to the largest eigenvalue of \( P_1 P_2 \). In a similar method, we can obtain the SVs of all signals corresponding to the virtual ULA.

3.2 Covariance matrix reconstruction

By using the estimated SVs of all signals \( \tilde{a}_j, j = 1, 2, \ldots, Q \), we proposed an efficient approach to reconstruct the INCM. The basic concept is to make use of the covariance matrix corresponding to virtual ULA, to estimate the power of the signals and noise. Then, the maximum correlation principle is used to transfer the SVs of the signals associated with the virtual array to the one corresponding to the physical sensors. Finally, by using the estimated SVs and the power of all signals and the noise power, a more accurate INCM is reconstructed.

It is well known that it cannot obtain a good power estimation by using Capon spectrum directly [32]. We take a single signal scenario.
as an example. The covariance matrix of the virtual array is written as
\[ \hat{R} = \sigma_n^2 \mathbf{a}(\theta) \mathbf{a}^H(\theta) + \sigma_n^2 \mathbf{I}_{M+1}. \] (20)
Then, the matrix inversion lemma is used to obtain \( \hat{R}^{-1} \) as
\[ \hat{R}^{-1} = \frac{1}{\sigma_n^2} \mathbf{I}_{M+1} - \frac{\sigma_n^2 \mathbf{a}(\theta) \mathbf{a}^H(\theta)}{\sigma_n^2 + (M + 1) \sigma_n^2}. \] (21)
Therefore, by using Capon spectrum, the estimated power of the signal is expressed as
\[ \hat{\sigma}_n^2 = \frac{1}{\mathbf{a}^H(\theta) \hat{R}^{-1} \mathbf{a}(\theta)} = \frac{1}{\sigma_n^2} + \frac{1}{M + 1} \left( \frac{1}{\sigma_n^2} + \frac{1}{\sigma_n^2} \right). \] (22)

Obviously, the estimated signal power includes the deviation term, i.e. \( 1/(M + 1) \sigma_n^2 \). Particularly, the estimation performance of power will degrade with the decrease of SNR.

Therefore, according to the modified version of Capon power estimation method in [13] [34] and the eigen-decomposition expression (10), the estimated SVs of signals are used to obtain the power of the jth signal by
\[ \hat{\sigma}_n^2 = \frac{1}{\mathbf{a}^H(\theta) \mathbf{a}(\theta)} = \frac{1}{\sigma_n^2} + \frac{1}{M + 1} \sum_{q=1}^{M+1} \lambda_q. \] (23)
which can reduce the effect of noise and hence provide a more precise power estimation. By using equation (10), the noise power \( \sigma_n^2 \) is estimated by
\[ \sigma_n^2 = \frac{1}{M + 1 - Q} \sum_{q=Q+1}^{M+1} \lambda_q. \] (24)

It is noted that the INCM cannot be directly reconstructed as
\[ \hat{R}_{\text{INCM}} = \sum_{j=2}^{Q} \hat{\sigma}_n^2 \mathbf{a}(\theta_j) \mathbf{a}^H(\theta_j) + \sigma_n^2 \mathbf{I}_{M+1}. \] (25)
since we cannot implement beamforming in the virtual array. In order to reconstruct the INCM on the actual physical array, we first convert \( \hat{\mathbf{a}} \in \mathbb{C}^{(M+1) \times 1} \) into the SV corresponding to real physical array as \( \mathbf{a}(\theta) \in \mathbb{C}^{(M+N+1) \times 1} \). Because of the different structure between the estimated \( \hat{\mathbf{a}} \) and \( \mathbf{a}(\theta) \) in (19) and (7), we first resort to the maximum correlation principle [14] [15] to obtain \( \mathbf{a}(\theta) \).

The computational cost of the proposed algorithm is dominated by the eigendecomposition operation in (10), (15) and (19), all of which require \( O((M + 1)^2) \). While the computational load of [13] [15] [16] [33] is \( O((M + N + 1)^2) \). That is to say that, compared with other subspace-based approaches, the proposed algorithm has a higher computational complexity. However, since it makes use of virtual array aperture of coprime array, the proposed method can provide more accurate estimations for the signal SV and the power, resulting in a more exact INCM reconstruction. As a result, the proposed algorithm can achieve a better performance than the methods being compared, as we will show through simulation results in the following section.

\section*{4 Simulation results}

In this section, let us consider a coprime array with a pair of coprime integers \( M = 3 \) and \( N = 5 \). The sensor positions of the two sparse subarrays are \([0, 3, 6, 9, 12]d\) and \([0, 5, 10, 15, 20, 25]d\), respectively, and both subarrays share the same reference position. That is to say, there are 10 identical omnidirectional sensors to deploy the coprime array. The unit element spacing \( d \) is half-wavelength. Assume that one DS and two interference signals impinge on the coprime array from the directions of \( \theta_1 = 0^\circ \), \( \theta_2 = 32.5^\circ \) and \( \theta_3 = 32.5^\circ \), respectively. Accordingly, the angle sectors of DS and interference signals are \( \Theta_1 = [\theta_1 - 4^\circ, \theta_1 + 4^\circ] \), \( \Theta_2 = [\theta_2 - 4^\circ, \theta_2 + 4^\circ] \) and \( \Theta_3 = [\theta_3 - 4^\circ, \theta_3 + 4^\circ] \), respectively. The additive noise model is a complex circularly symmetric zero-mean Gaussian random process. The INRs of two interference are 10dB. For each simulation point, 50 Monte Carlo runs are performed.

For performance comparison, since the proposed algorithm is an improved version of the INCM-based subspace projection (SP) (INCM-SP) beamformer [16], we will compare with it in detail. Besides, the conventional eigenspace (CE) beamformer [33], the worst case (WC) beamformer [5], the INCM-based quadratically constrained quadratic programming (INCM-QCQP) beamformer [11], the interference cancellation (IC) beamformer [13], and the correlation reconstruction (CR) beamformer [15] are also presented. The number of signals is assumed to be correctly estimated for subspace-based methods. For the worst case beamformer, the uncertainty parameter is set as \( \epsilon = 0.2 \times (M + N - 1) \). In order to ensure a fair comparison, for each compared method, all parameters are chosen to achieve the best performance.

\begin{example}
\textbf{Example 1} : \textit{Exactly known signal SVs}: In this example, we consider the scenario that the SVs of the DS and the interference signals are
\end{example}
respectively. Whereas we assume them as known. The output SINRs of all methods versus the input SNR are presented in Fig. 1(a), where the number of snapshots is 100. From Fig. 1(a), it is observed that the proposed algorithm, INCM-SP and INCM-QCQP have nearly the same output SINRs, and are superior to CE, WC, IC and CR. Overall, the reconstruction-based approaches outperform the non-reconstruction-based ones. It is also noted that, with known SV information, the proposed algorithm, INCM-SP and INCM-QCQP can approach the optimal output SINR, while CE, WC, IC and CR cannot keep near-optimal performance with the increase of input SNR. The reason is explained that the non-reconstruction-based approaches directly use SCM to design adaptive beamformer. However, SCM contains DS component, which could make the beamformer to suppress DS instead of enhancing it, especially in high SNIR case. Fig. 1(b) depicts the output SINR of each method versus snapshot numbers, where the input SNR is 10 dB. In Fig. 1(b), it is shown that the proposed algorithm, INCM-SP and INCM-QCQP not only have faster convergence speeds, but also larger output SINRs than other methods. Furthermore, we find that among reconstruction-based approaches, the proposed algorithm and INCM-SP have a similar convergence performance and approach the optimal SINR.

**Example 2 : Fixed signal SV mismatch:** Look direction mismatch will degrade beamformer performance. In this example, we consider the case that there is a direction mismatch between assumed look direction of DS and actual one. In detail, the actual look directions of DS and interferences are $\theta_1 = 0^\circ$, $\theta_2 = 32.5^\circ$ and $\theta_3 = -32.5^\circ$, respectively. Whereas we assume them as $\theta_1 = 4^\circ$, $\theta_2 = 36.5^\circ$ and $\theta_3 = -36.5^\circ$, respectively. That is to say, there is a 4$^\circ$ look direction mismatch for each signal. The output SINR curves for all methods versus input SNR are shown in Fig. 2(a). In Fig. 2(a), it is seen that, similar to Fig. 1(a), the proposed algorithm has almost the same output SINRs as INCM-SP and is very close to the theoretical optimal SINR. It is also observed that the proposed algorithm outperforms INCM-QCQP. CE, WC, IC and CR beamformers. Furthermore, it is seen that, due to the signal SV mismatch, CE and IC exhibit performance degradation in both low and high SNR regions. Fig. 2(b) depicts the output SINRs of the proposed and the other algorithms versus the number of snapshots. As observed from Fig. 2(b), the proposed algorithm presents a faster convergence speed and a higher output SINR than all other beamformers. Similar to Fig. 1(b), the proposed algorithm and INCM-SP have nearly overlapping output SINRs as INCM-SP and is very close to the optimal output SINR as the optimal value. The performance difference between the proposed algorithm and INCM-SP will be shown in the next example.

**Example 3 : Increased interference number with fixed look direction mismatch:** In this example, we add two more interferers with 10dB input INR from the directions of $\theta_4 = 65^\circ$ and $\theta_5 = -65^\circ$, respectively, and their directions are assumed as $\theta_4 = 61^\circ$ and $\theta_5 = -61^\circ$, respectively. Accordingly, their angle sectors are $\Theta_4 = [\theta_4 - 4^\circ, \theta_4 + 4^\circ]$ and $\Theta_5 = [\theta_5 - 4^\circ, \theta_5 + 4^\circ]$, respectively. Other simulation settings are identical with Example 2. From Fig. 3(a), it is seen that, to some degree, the performance of all methods degrades because of the increased number of interferers. It is also observed in Fig. 3(a) that the proposed algorithm has the best output SINR performance among all methods and approaches the optimal value similar to Example 1 and Example 2. This is due to
the fact that the proposed algorithm takes advantage of the virtual array aperture which equivalently increases the number of sensors, thus obtaining a higher angle resolution. Fig. 3(a) illustrates that the proposed algorithm has a better performance than other methods in terms of the output SINR and the convergence speed.

Example 4: Random signal direction mismatch: In this example, we assume that DS has a random look direction mismatch. More specifically, the look direction mismatch of the DS is randomly distributed in $[-4^\circ, 4^\circ]$. Other simulation settings are identical to the last example. Note that the look directions of all signals change from trial to trial but keep fixed from snapshot to snapshot. In Fig. 4(a), it is observed that, similar to the previous example, the proposed algorithm still outperforms other methods due to its ability to estimate the SVs of DS and interference signals more accurately than other beamformers. As compared to other eigenspace-based methods, CE and IC present a worse performance. CR has a SINR drop when the input SNR is close to the INR. INCM-SP is sensitive to the number of interferers and there is a performance degradation with interference number increases. The proposed algorithm can achieve a better performance in both low and high input SNR regions. The input SINRs of all approaches versus snapshots are shown in Fig. 4(b). It is seen that, clearly, the proposed algorithm can converge to the steady-state fast and achieves a near-optimal SINR performance. Therefore, the proposed algorithm has a better robustness under the condition where the look directions of signals have a random mismatch.

5 Conclusion

A novel robust adaptive beamforming algorithm is proposed for coprime array in this paper. According to the projection method, the actual SVs of the DS and the interference signals are estimated from an intersection of two subspaces. Moreover, their power is obtained by using the covariance fitting approach. Then, the maximum correlation principle is used to reconstruct the INCM based on the physical array rather than the virtual one. Since coprime array has a larger array aperture than ULA with the same number of physical sensors, the proposed algorithm can obtain more accurate estimation for DOAs and power of signals, leading to a more precise INCM reconstruction. Finally, with the estimated DS SV and INCM, the proposed adaptive beamformer is formulated in accordance with the MVDR criterion. Simulation results clearly demonstrate that the proposed algorithm provides a better performance than existing subspace-based adaptive beamformers.

6 Acknowledgments

The work of K. Liu was supported by the China Scholarship Council for his stay at the Temple University. The work of Y. D. Zhang was supported in part by the National Science Foundation under Grant No. AST-1547420.
References


© The Institution of Engineering and Technology 2015