

Research Article

Joint DOA and DOD Estimation in Bistatic MIMO Radar without Estimating the Number of Targets

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Existing subspace-based direction finding methods for multiple-input multiple-output (MIMO) radar assume perfect knowledge about the dimension of the signal or noise subspace, which is hard to be established without prior knowledge of the signal environment. In this paper, an efficient method for joint DOA and DOD estimation in bistatic MIMO radar without estimating the number of targets is presented. The proposed method computes an estimate of the noise subspace using the power of R (POR) technique. Then the two-dimensional (2D) direction finding problem is decoupled into two successive one-dimensional (1D) angle estimation problems by employing the rank reduction (RARE) estimator.

1. Introduction

MIMO radar employs multiple transmit antennas for transmitting several orthogonal waveforms and multiple receive antennas for receiving the echoes reflected by the targets [1–3]. MIMO radar can exploit the waveform diversity to form a virtual array with increased degrees of freedom (DOFs) and a larger aperture compared to the traditional phased-array radar. It has been shown that MIMO radar can provide enhanced spatial resolution, achieve better target detection performance, and significantly improve the system's parameter identifiability [1–6].

Many direction finding methods have been proposed (see [7–11] for details) for MIMO radar. In [9], the estimation of signal parameters via rotational invariance technique (ESPRIT) was used for angle estimation in bistatic MIMO radar. The multiple signal classification (MUSIC) [12] algorithm, one of the most representative subspace methods, can also be used for direction finding in bistatic MIMO radar. However, the requirement of 2D search of 2D-MUSIC for spectral peaks leads to much higher computational complexity. To mitigate this problem, many joint DOA and DOD estimation methods have been proposed (see [8, 10, 11]

for details). The aforementioned direction finding methods for bistatic MIMO radar are based on the noise or signal subspace. Thus, the number of targets, that is, the dimension of the signal subspace, has to be known *a priori*. The most representative algorithms for estimating the number of sources are Akaike information criterion (AIC) and minimum description length (MDL) [13]. However, experimental evidence shows that the two criteria cannot give accurate estimation results for a small sample size and a low signal-to-noise ratio (SNR) [14–16]. Hence, the existing subspace-based direction finding methods for bistatic MIMO radar may be unrealistic. To avoid source number estimation, in [17], the Capon estimator of [18] was used for direction finding in MIMO radar. However, the Capon estimator cannot achieve resolution as high as that of the MUSIC algorithm [13].

In this work, we address the problem of joint DOA and DOD estimation in bistatic MIMO radar without estimating the number of targets. To eliminate the need to estimate the dimension of the noise subspace explicitly, the POR technique is employed to compute an estimate of the noise subspace. The POR technique requires the inverse of the sample covariance matrix. Due to finite sample effect, however,

the sample covariance matrix may be either singular or ill-conditioned. To guarantee that the sample covariance matrix is invertible, a completely automatic diagonal loading (ADL) method introduced in [19], which computes the diagonal loading (DL) level automatically from the received data without specifying any user parameter, is utilised to estimate a well-conditioned sample covariance matrix. In addition, based on the RARE estimator for direction finding in partly calibrated arrays [20], the 2D angle estimation problem is then decoupled into two successive 1D angle estimation problems.

This paper is organised as follows. In Section 2, the signal model for bistatic MIMO radar is provided. In Section 3, a brief overview of 2D-MUSIC, ESPRIT, and reduced-dimension MUSIC (RD-MUSIC) for direction finding in bistatic MIMO radar is given. The proposed method is given in Section 4. Simulation results are presented in Section 5 and conclusions are drawn in Section 6.

2. Signal Model for Bistatic MIMO Radar

Consider a bistatic MIMO radar system with a ULA of M antennas used for transmitting and a ULA of N antennas used for receiving. The M transmit antennas are used to transmit M orthogonal waveforms. Consequently, the output of the matched filters of MIMO radar at the n th snapshot can be written as [4, 8]:

$$\begin{aligned} \mathbf{x}[n] &= \sum_{l=1}^P \mathbf{a}_r(\psi_l) \otimes \mathbf{a}_t(\theta_l) b_l[n] + \mathbf{n}[n] \\ &= \sum_{l=1}^P \mathbf{a}(\psi_l, \theta_l) b_l[n] + \mathbf{n}[n] \\ &= \mathbf{A}\mathbf{b}[n] + \mathbf{n}[n], \end{aligned} \quad (1)$$

where $\{\psi_l, \theta_l\}_{l=1}^P$ are the DOAs and DODs of the targets with respect to the receive array normal and transmit array normal, respectively; \otimes stands for the Kronecker product operator, $\mathbf{a}(\psi_l, \theta_l) = \mathbf{a}_r(\psi_l) \otimes \mathbf{a}_t(\theta_l)$;

$$\begin{aligned} \mathbf{a}_t(\theta_l) &= [1, e^{j\phi_t(\theta_l)}, \dots, e^{j(M-1)\phi_t(\theta_l)}]^T, \\ \mathbf{a}_r(\psi_l) &= [1, e^{j\phi_r(\psi_l)}, \dots, e^{j(N-1)\phi_r(\psi_l)}]^T \end{aligned} \quad (2)$$

are the transmit and receive steering vectors for θ_l and ψ_l , with $\phi_t(\theta_l) = 2\pi d_t \sin(\theta_l)/\lambda$ and $\phi_r(\psi_l) = 2\pi d_r \sin(\psi_l)/\lambda$, where d_t and d_r are the interelement spacings of the transmit and receive arrays and λ is signal wavelength; $b_l[n] = \beta_l e^{j2\pi f_l n}$, with β_l being the complex-valued reflection coefficient of the l th target and f_l being Doppler frequency; $\mathbf{b}[n] = [b_1[n], b_2[n], \dots, b_P[n]]^T$;

$$\mathbf{A} = [\mathbf{a}(\psi_1, \theta_1), \dots, \mathbf{a}(\psi_P, \theta_P)] \quad (3)$$

is the overall transmit-receive or virtual array manifold, and $\mathbf{n}[n]$ is the received complex-valued white noise with a power σ^2 .

Due to the time-varying properties of the reflection coefficients and the fact that the Doppler frequencies satisfy $f_1 \neq f_2 \neq \dots \neq f_P$ and are well-separated, we assume that all target-reflected signals and noise are uncorrelated. Then the data covariance matrix can be expressed as

$$\begin{aligned} \mathbf{R}_x &= E[\mathbf{x}[n] \mathbf{x}[n]^H] \\ &= \mathbf{A}\mathbf{S}\mathbf{A}^H + \sigma^2 \mathbf{I} \\ &= \mathbf{U}_s \Lambda \mathbf{U}_s^H + \sigma^2 \mathbf{U}_n \mathbf{U}_n^H, \end{aligned} \quad (4)$$

where $E[\cdot]$ and $[\cdot]^H$ denote expectation and Hermitian transpose, respectively; $\mathbf{S} = \text{diag}\{\sigma_1^2, \dots, \sigma_P^2\}$ is the signal covariance matrix, with σ_l^2 being the variance of the l th source; \mathbf{I} is the identity matrix, $\Lambda = \text{diag}\{\lambda_1 + \sigma^2, \dots, \lambda_P + \sigma^2\}$ consists of the P principal eigenvalues of \mathbf{R}_x , \mathbf{U}_s is the signal subspace, specified by the principal eigenvectors of \mathbf{R}_x , and the remaining eigenvectors \mathbf{U}_n are the noise subspace. In practice, the sample covariance matrix of (4),

$$\widehat{\mathbf{R}}_x = \frac{1}{L} \sum_{n=1}^L \mathbf{x}[n] \mathbf{x}[n]^H, \quad (5)$$

is used, where L is the number of snapshots.

3. Review of 2D-MUSIC, ESPRIT, and RD-MUSIC

3.1. *2D-MUSIC*. The 2D-MUSIC algorithm can be constructed as [8]:

$$f(\psi, \theta) = \frac{1}{[\mathbf{a}_r(\psi) \otimes \mathbf{a}_t(\theta)]^H \mathbf{U}_n \mathbf{U}_n^H [\mathbf{a}_r(\psi) \otimes \mathbf{a}_t(\theta)]}. \quad (6)$$

The P largest peaks of $f(\psi, \theta)$ indicate the DOA and DOD estimates of the targets. 2D-MUSIC algorithm requires a 2D search, which yields a high computational cost.

3.2. *ESPRIT*. For ESPRIT-based estimator [9], it is based on the signal subspace \mathbf{U}_s . Let $\mathbf{U}_{s,1}$ be the subset of \mathbf{U}_s , which relates from the first to the $(M-1)$ th transmit antennas, and $\mathbf{U}_{s,2}$ be the subset of \mathbf{U}_s , which relates from the second to the M th transmit antennas. We then have the following relationship:

$$\mathbf{U}_{s,2} = \mathbf{U}_{s,1} \mathbf{T}_e \mathbf{Q}_e \mathbf{T}_e^{-1}, \quad (7)$$

where \mathbf{T}_e is an unknown nonsingular matrix and \mathbf{Q}_e is a diagonal matrix, with $e^{j2\pi d_l \sin(\theta_l)/\lambda}$ being its l th main diagonal element. Thus, the DODs can be found from the eigenvalues

of $(\mathbf{U}_{s,1}^H \mathbf{U}_{s,1})^{-1} \mathbf{U}_{s,1}^H \mathbf{U}_{s,2}$. Similarly, by using the rotational invariance property between the receive steering vectors associated with the first $N - 1$ and last $N - 1$ antennas, the DOAs can be obtained easily using the ESPRIT-based method.

3.3. *RD-MUSIC*. To reduce the computational complexity of the 2D-MUSIC algorithm, the RD-MUSIC algorithm was proposed [8]:

$$\begin{aligned} & \min [\mathbf{a}_r(\psi) \otimes \mathbf{a}_t(\theta)]^H \mathbf{U}_n \mathbf{U}_n^H [\mathbf{a}_r(\psi) \otimes \mathbf{a}_t(\theta)] \\ & = \min_{\psi} \mathbf{a}_t(\theta)^H \mathbf{Q}(\psi) \mathbf{a}_t(\theta), \end{aligned} \quad (8)$$

$$\text{subject to } \mathbf{e}^H \mathbf{a}_t(\theta) = 1,$$

where $\mathbf{Q}(\psi) = [\mathbf{a}_r(\psi) \otimes \mathbf{I}]^H \mathbf{U}_n \mathbf{U}_n^H [\mathbf{a}_r(\psi) \otimes \mathbf{I}]$ and $\mathbf{e} = [1, 0, \dots, 0]^T$ is the $M \times 1$ vector.

Using the Lagrange method, the solution to the problem (8) is given by

$$\mathbf{a}_t(\theta) = \frac{\mathbf{Q}(\psi)^{-1} \mathbf{e}}{\mathbf{e}^H \mathbf{Q}(\psi)^{-1} \mathbf{e}}. \quad (9)$$

Substituting $\mathbf{a}_t(\theta)$ of (9) into $\min \mathbf{a}_t(\theta)^H \mathbf{Q}(\psi) \mathbf{a}_t(\theta)$, the DOAs can then be estimated via

$$\min_{\psi} \frac{1}{\mathbf{e}^H \mathbf{Q}(\psi) \mathbf{e}} = \max_{\psi} \mathbf{e}^H \mathbf{Q}(\psi) \mathbf{e}. \quad (10)$$

The P largest peaks $(\hat{\psi}_1, \hat{\psi}_2, \dots, \hat{\psi}_P)$ of $\mathbf{e}^H \mathbf{Q}(\psi) \mathbf{e}$ indicate the DOAs, and we also obtain P vectors $\hat{\mathbf{a}}_t(\theta_1), \hat{\mathbf{a}}_t(\theta_2), \dots, \hat{\mathbf{a}}_t(\theta_P)$ according to (9). Using the obtained $\{\hat{\mathbf{a}}_t(\theta_i)\}_{i=1}^P$, we can compute the DOD estimate corresponding to each DOA estimate of $\{\hat{\psi}_i\}_{i=1}^P$ (see [8] for details).

The RD-MUSIC undergoes the following limitations. First, the RD-MUSIC fails when multiple targets share the same DOA but have different DODs. Second, it cannot be always guaranteed that the matrix $\mathbf{Q}(\psi)$ is invertible. It can be proved that the matrix $\mathbf{Q}(\psi)$ may be either singular or ill-conditioned.

Proof. In the ideal case of exactly known \mathbf{R}_x , the DOAs and DODs can be found from the following equation:

$$\begin{aligned} & \mathbf{a}_t(\theta)^H [\mathbf{a}_r(\psi) \otimes \mathbf{I}]^H \mathbf{U}_n \mathbf{U}_n^H [\mathbf{a}_r(\psi) \otimes \mathbf{I}] \mathbf{a}_t(\theta) \\ & = \mathbf{a}_t(\theta)^H \mathbf{Q}(\psi) \mathbf{a}_t(\theta) = 0. \end{aligned} \quad (11)$$

Since $\mathbf{a}_t(\theta) \neq \mathbf{0}$, (11) can hold true only if the matrix $\mathbf{Q}(\psi)$ drops rank; that is,

$$\text{rank}\{\mathbf{Q}(\psi)\} < M. \quad (12)$$

From the above analysis, it follows that the matrix $\mathbf{Q}(\psi)$ may be either singular or ill-conditioned. Therefore, a small DL factor should be loaded into $\mathbf{Q}(\psi)$ to guarantee that it is invertible. \square

4. Proposed Method

4.1. *Estimating Noise Subspace*. To avoid the need of source number estimation, the POR technique estimates the noise subspace of \mathbf{R}_x based on \mathbf{R}_x^{-m} [21]. Consider the following equation:

$$\sigma^{2m} \mathbf{R}_x^{-m} = \mathbf{U}_n \mathbf{U}_n^H + \mathbf{U}_s \text{diag} \left\{ \left(\frac{\sigma^2}{\lambda_i^2 + \sigma^2} \right)^m \right\} \mathbf{U}_s^H, \quad (13)$$

where m is a positive integer. Clearly, $(\sigma^2/(\lambda_i^2 + \sigma^2))$ is less than 1; thus $(\sigma^2/(\lambda_i^2 + \sigma^2))^m$ converges to zero for sufficiently large m . Theoretically, we have [21]:

$$\lim_{m \rightarrow \infty} \sigma^{2m} \mathbf{R}_x^{-m} = \mathbf{U}_n \mathbf{U}_n^H. \quad (14)$$

Therefore, the POR technique obtains an estimate of the noise subspace without knowledge about the number of targets.

It should be noted that the POR technique is not applicable when $L < NM$, because if $L < NM$ snapshots are used to form $\hat{\mathbf{R}}_x$, $MN - L$ eigenvalue estimates are zero [22]. In such a case, $\hat{\mathbf{R}}_x$ is rank deficient and is not invertible. To overcome this problem, we suggest using the ADL method introduced in [19] to estimate an enhanced covariance matrix. The essence behind the ADL is to replace the sample covariance matrix by an enhanced estimate obtained via a shrinkage method. The shrinkage-based covariance matrix estimate is a general linear combination of the sample covariance matrix and the identity matrix [19, 23]:

$$\tilde{\mathbf{R}}_x = \alpha \mathbf{I} + \beta \hat{\mathbf{R}}_x, \quad (15)$$

where $\tilde{\mathbf{R}}_x$ and $\hat{\mathbf{R}}_x$ are the enhanced estimate and sample estimate of the actual covariance matrix \mathbf{R}_x , respectively, and $\alpha \geq 0$ and $\beta \geq 0$ are the shrinkage parameters, which can be obtained by minimising the mean-squared error (MSE) of $\tilde{\mathbf{R}}_x$:

$$\begin{aligned} \text{MSE}(\tilde{\mathbf{R}}_x) &= E \left\{ \|\tilde{\mathbf{R}}_x - \mathbf{R}_x\|_F^2 \right\} \\ &= \|\alpha \mathbf{I} - (1 - \beta) \mathbf{R}_x\|_F^2 + \beta^2 E \left\{ \|\hat{\mathbf{R}}_x - \mathbf{R}_x\|_F^2 \right\} \\ &= \alpha^2 M + 2\alpha(1 - \beta) \text{tr}(\mathbf{R}_x) + (1 - \beta)^2 \|\mathbf{R}_x\|_F^2 \\ &\quad + \beta^2 E \left\{ \|\hat{\mathbf{R}}_x - \mathbf{R}_x\|_F^2 \right\}, \end{aligned} \quad (16)$$

where $\text{tr}(\cdot)$ and $\|\cdot\|_F$ denote the trace operator and the Frobenius norm, respectively. As suggested in [19, 23], the estimates of α and β can be obtained as

$$\begin{aligned} \hat{\alpha} &= \min \left[\frac{\hat{\nu} \hat{\rho}}{\|\hat{\mathbf{R}}_x - \hat{\nu} \mathbf{I}\|_F^2}, \hat{\nu} \right], \\ \hat{\beta} &= 1 - \frac{\hat{\alpha}}{\hat{\nu}}, \end{aligned} \quad (17)$$

where

$$\begin{aligned}\hat{\nu} &= \frac{\text{tr}(\widehat{\mathbf{R}}_x)}{MN} \\ \hat{\rho} &= \frac{1}{L^2} \sum_{n=1}^L \|\mathbf{x}[n]\|^4 - \frac{1}{L} \|\widehat{\mathbf{R}}_x\|_F^2.\end{aligned}\quad (18)$$

4.2. *Performing Angle Estimation.* Substituting $\widetilde{\mathbf{R}}_x^{-m}$ into (11) to replace $\mathbf{U}_n \mathbf{U}_n^H$, we have

$$\begin{aligned}\mathbf{a}_t(\theta)^H [\mathbf{a}_r(\psi) \otimes \mathbf{I}]^H \widetilde{\mathbf{R}}_x^{-m} [\mathbf{a}_r(\psi) \otimes \mathbf{I}] \mathbf{a}_t(\theta) \\ = \mathbf{a}_t(\theta)^H \widehat{\mathbf{Q}}(\psi) \mathbf{a}_t(\theta) = 0.\end{aligned}\quad (19)$$

Since $\mathbf{a}_t(\theta) \neq \mathbf{0}$, (19) holds true only if the matrix $\widehat{\mathbf{Q}}(\psi)$ drops rank so that

$$\text{rank}\{\widehat{\mathbf{Q}}(\psi)\} < M. \quad (20)$$

Note that if $\text{rank}(\widetilde{\mathbf{R}}_x^{-m}) \geq \text{rank}(\mathbf{a}_r(\psi) \otimes \mathbf{I})$, that is, $MN - P \geq M$, in general, $\widehat{\mathbf{Q}}(\psi)$ is a full rank, and the reduction of the rank of $\widehat{\mathbf{Q}}(\psi)$ will take place on the true DOAs [20]. In this case, the minimal eigenvalue of $\widehat{\mathbf{Q}}(\psi)$ will tend to have a minimum when ψ coincides with one of the DOAs ψ_l , $l = 1, \dots, P$ [24]. Therefore, the P highest peaks of

$$\frac{1}{\mathcal{M}[\widehat{\mathbf{Q}}(\psi)]} \quad (21)$$

indicate the DOAs, where $\mathcal{M}[\cdot]$ denotes the operator that yields the minimal eigenvalue of a matrix.

After obtaining the DOA estimates, we then utilise an appropriate modification of the spectral MUSIC algorithm to obtain the DOD estimates. By exploiting the DOA estimates $\{\widehat{\psi}_l\}_{l=1}^P$ given by (21), the corresponding DODs $\{\theta_l\}_{l=1}^P$ can be estimated from the highest peaks of the following function:

$$f(\psi_l, \theta) = \frac{1}{\mathbf{a}_t(\theta)^H \widehat{\mathbf{Q}}(\psi_l) \mathbf{a}_t(\theta)}, \quad l = 1, \dots, P. \quad (22)$$

It is worth noting that two successive 1D searching are required only for finding the angle estimates of $(\psi_l, \theta_l)_{l=1}^P$, leading to significant reduction of its computational cost

compared with the traditional 2D spectral searching algorithms.

4.3. *Cramér-Rao Bound.* In this subsection, we derive the stochastic Cramér-Rao bound (CRB) for joint DOA and DOD estimation by extending the results of [20].

Define the $2P \times 1$ vector $\boldsymbol{\eta} = [\boldsymbol{\psi}^T, \boldsymbol{\theta}^T]^T$ containing the unknown parameters, where

$$\begin{aligned}\boldsymbol{\psi} &= [\psi_1, \dots, \psi_P]^T, \\ \boldsymbol{\theta} &= [\theta_1, \dots, \theta_P]^T.\end{aligned}\quad (23)$$

The snapshots are assumed to satisfy the following stochastic model:

$$\mathbf{x}[n] = \mathcal{N}\{\mathbf{0}, \mathbf{R}_x\}, \quad (24)$$

where $\mathcal{N}\{\cdot, \cdot\}$ is the complex Gaussian distribution. The unknown parameters of the problem include the elements of the vector $\boldsymbol{\eta}$, the noise variance σ^2 , and the parameters of the source covariance matrix $\{\mathbf{S}_{ii}\}_{i=1}^P$ and $\{\text{Re}\{\mathbf{S}_{ij}\}, \text{Im}\{\mathbf{S}_{ij}\}; j > i\}_{i,j=1}^P$.

Considering the problem with respect to the parameters of the source covariance matrix and the noise variance, the $2P \times 2P$ Fisher information matrix can be written as [20]:

$$[\text{CRB}^{-1}(\boldsymbol{\eta})]_{i,j} = \frac{2L}{\sigma^2} \text{Re} \left\{ \text{tr} \left(\mathbf{W} \frac{\partial \mathbf{A}^H}{\partial \eta_j} \mathbf{P}_A^\perp \frac{\partial \mathbf{A}}{\partial \eta_i} \right) \right\}, \quad (25)$$

where

$$\mathbf{P}_A^\perp = \mathbf{I} - \mathbf{A}(\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \quad (26)$$

is the $MN \times MN$ orthogonal projection matrix and the $P \times P$ matrix

$$\mathbf{W} = \mathbf{S}(\mathbf{A}^H \mathbf{A} \mathbf{S} + \sigma^2 \mathbf{I})^{-1} \mathbf{A}^H \mathbf{A} \mathbf{S}. \quad (27)$$

After straightforward derivations using (25) and combining them in a compact matrix form, the CRB matrix can be expressed as

$$\text{CRB} = \frac{\sigma^2}{2L} \left[\text{Re} \left\{ (\mathbf{1}\mathbf{1}^T \otimes \mathbf{W}) \odot (\mathbf{D}^H \mathbf{P}_A^\perp \mathbf{D})^T \right\} \right]^{-1}, \quad (28)$$

where \odot denotes the Schur-Hadamard matrix product and $\mathbf{1}$ is the 2×1 vector of ones. Here, the matrix \mathbf{D} is defined as

$$\mathbf{D} = [\mathbf{D}_\psi, \mathbf{D}_\theta], \quad (29)$$

where

$$\begin{aligned}\mathbf{D}_\psi &= \left[\frac{\partial(\mathbf{a}(\psi_1, \theta_1))}{\partial \psi_1}, \dots, \frac{\partial(\mathbf{a}(\psi_P, \theta_P))}{\partial \psi_P} \right], \\ \mathbf{D}_\theta &= \left[\frac{\partial(\mathbf{a}(\psi_1, \theta_1))}{\partial \theta_1}, \dots, \frac{\partial(\mathbf{a}(\psi_P, \theta_P))}{\partial \theta_P} \right].\end{aligned}\quad (30)$$

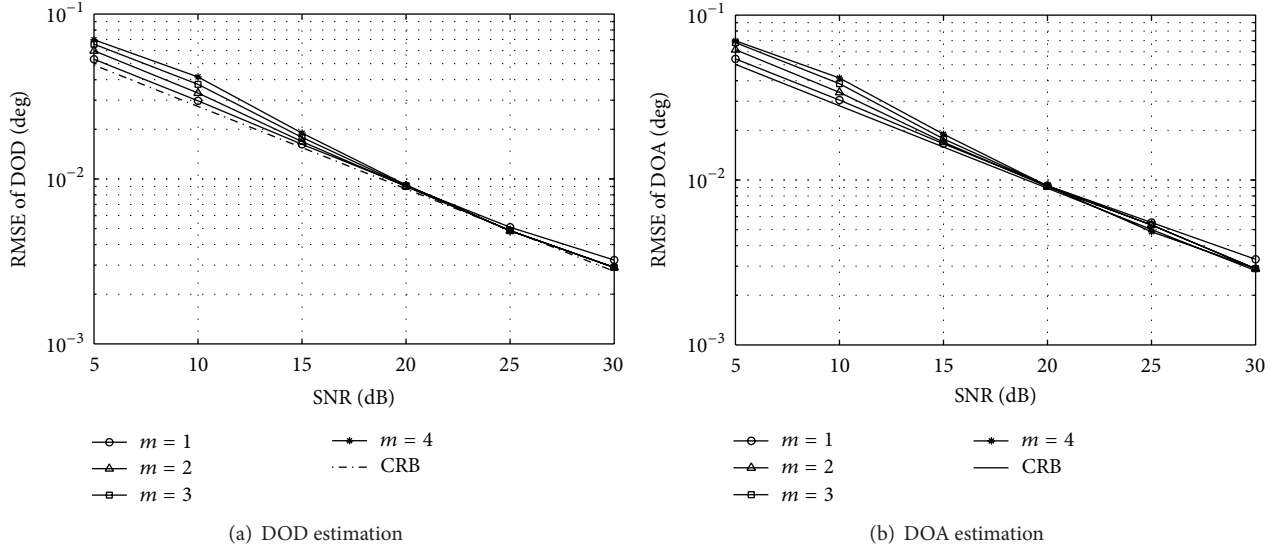


FIGURE 1: RMSEs of angle estimation against input SNR.

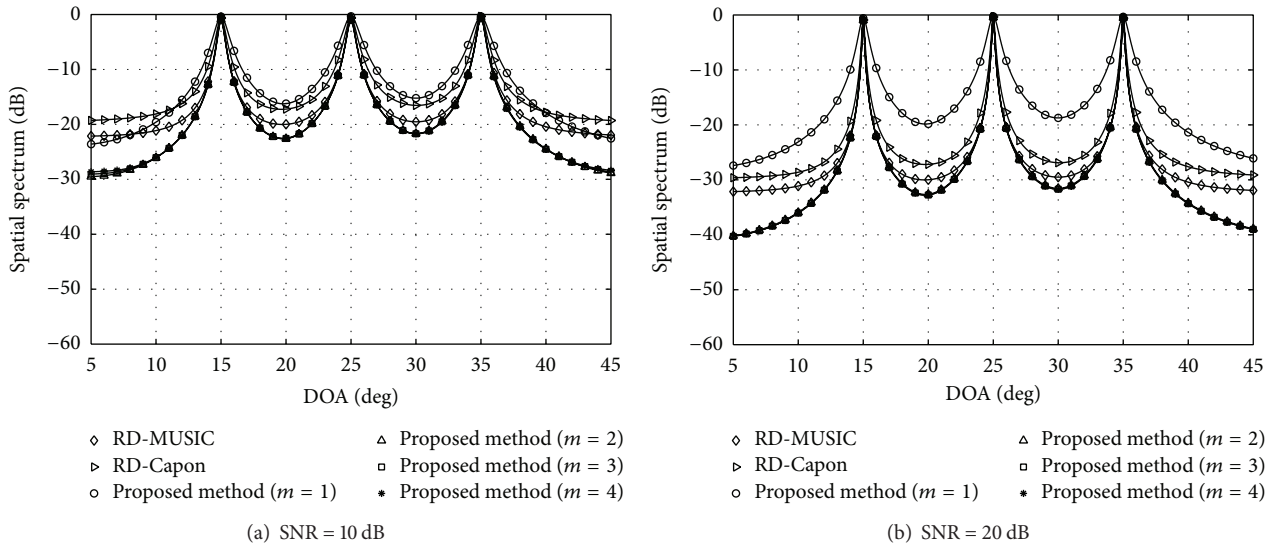


FIGURE 2: Spatial spectrum of DOA estimation.

5. Simulations

In this section, simulations are carried out to investigate the performance of the proposed method compared with the 2D-MUSIC, ESPRIT-based of [9], RD-Capon of [17], and the RD-MUSIC of [8]. We consider a bistatic MIMO radar system where a ULA of $M = 8$ antennas is used for transmitting and a ULA of $N = 8$ antennas is used for receiving. Both of these ULAs are arranged with half-wavelength spacing between adjacent antennas. Three noncoherent targets with the same signal-to-noise ration (SNR) are located at angles $(\psi_1, \theta_1) = (15^\circ, 10^\circ)$, $(\psi_2, \theta_2) = (25^\circ, 20^\circ)$, and $(\psi_3, \theta_3) = (35^\circ, 30^\circ)$, respectively. The additive noises are spatially and temporally white. The input SNR of the l th source is defined as

$10\log_{10}(\sigma_l^2/\sigma^2)$. All results are averaged over 500 simulation runs. Define the root mean squared error (RMSE) as

$$\frac{1}{P} \sum_{l=1}^P \sqrt{\frac{1}{500} \sum_{n=1}^{500} (\vartheta_l - \hat{\vartheta}_{n,l})^2}, \quad (31)$$

where $\hat{\vartheta}_{n,l}$ is the estimate of DOA/DOD ϑ_l of the n th run.

Figure 1 shows the effect of the parameter m on the performance of the proposed method for $L = 100$. As shown, the proposed method with a small m has better estimation accuracy at the low SNR region. As the input SNR increases, the proposed method with a large m outperforms the one with a small m . Figure 2 presents the spatial spectrum of

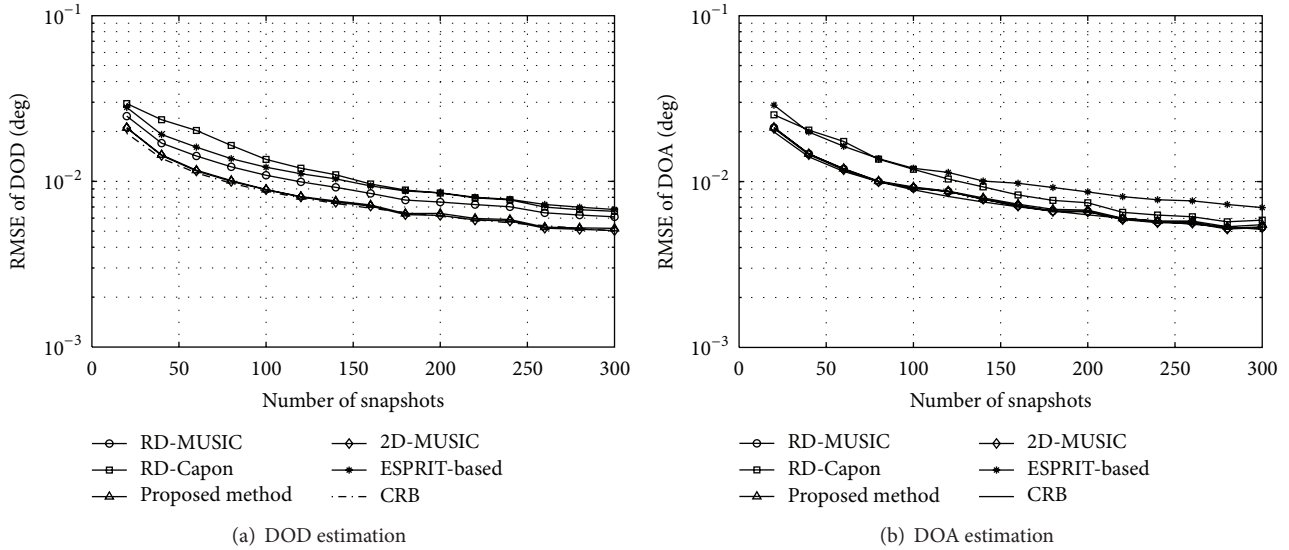


FIGURE 3: RMSEs of angle estimation against the number of snapshots.

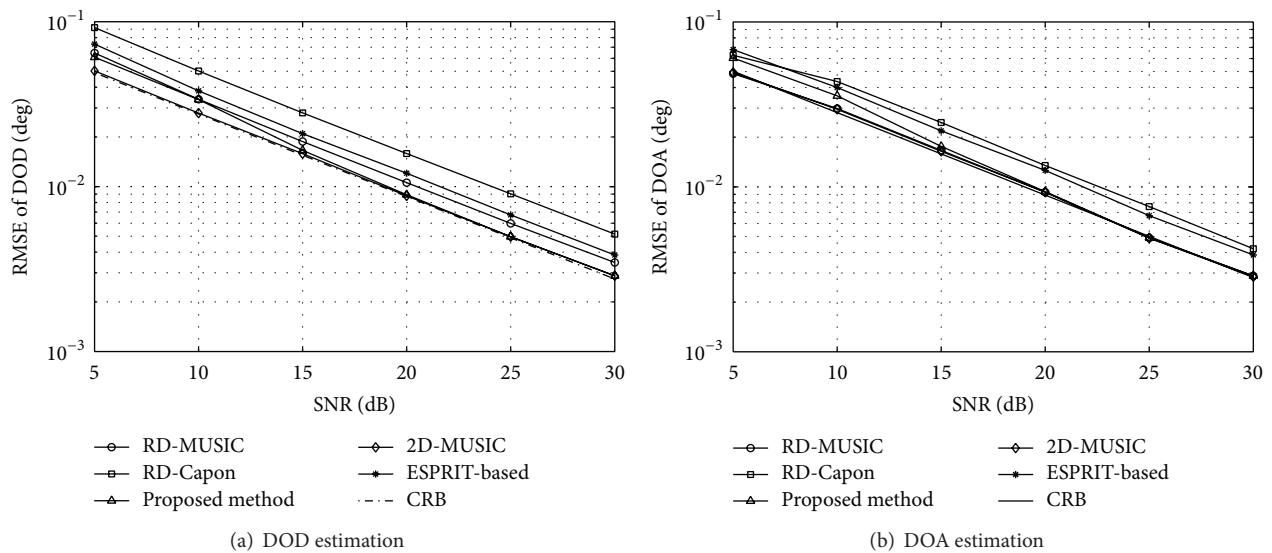


FIGURE 4: RMSEs of angle estimation against input SNR.

DOA estimation of the RD-MUSIC, the RD-Capon, and the proposed method. It can be clearly seen that the proposed method with $m > 1$ and the RD-MUSIC achieve similar resolution, which is higher than that of the RD-Capon. From the results of Figures 1 and 2, in the following examples we will choose $m = 2$ for the proposed method.

Figure 3 shows the RMSEs of angle estimation against the number of snapshots for SNR = 20 dB. Clearly the proposed method has achieved similar performance as the 2D-MUSIC. Figure 4 shows the RMSEs as a function of SNR for $L = 100$. It can be seen from Figure 4 that as the input SNR increases, the estimation performance of the proposed method is close to that of the 2D-MUSIC. In addition, compared to the RD-MUSIC, more accurate DOD estimation is obtained by the proposed method at the expense of high computational cost.

To see more clearly the performance of the proposed algorithm, we plot RMSEs against separation angle between the second and third targets in Figure 5, where SNR = 20 dB and $L = 100$, respectively. Three targets are assumed to be located at $(\psi_1 = 15^\circ, \theta_1 = 10^\circ)$, $(\psi_2 = 25^\circ, \theta_2 = 20^\circ)$, and $(\psi_3 = 25^\circ + \Delta, \theta_3 = 20^\circ + \Delta)$, where Δ varies from 4° to 20° . It is observed that as the separation angle Δ increases, the performance of the proposed method and the 2D-MUSIC are very similar.

6. Conclusions

The problem of joint DOA and DOD estimation in bistatic MIMO radar has been studied. To avoid the need of source number estimation, the POR technique is utilised to compute

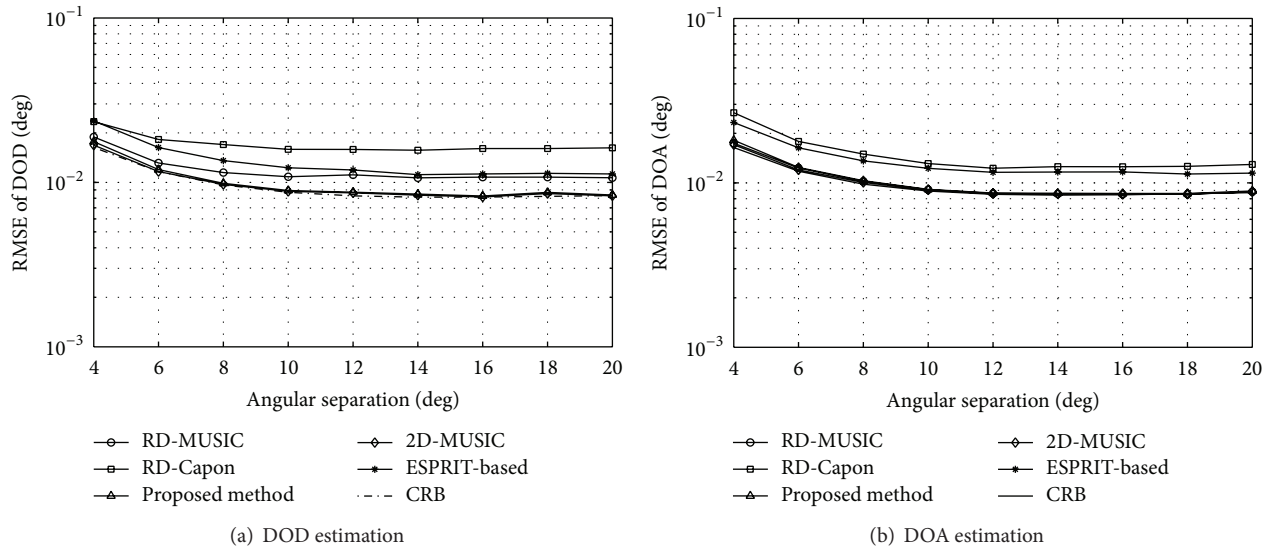


FIGURE 5: RMSEs of angle estimation against angular separation.

an estimate of the noise subspace. We then apply the spectral RARE technique to transform the complicated 2D searching process into two 1D searches. The effectiveness of the proposed method has been demonstrated by simulation results.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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