RANDOM MATRIX BASED METHOD FOR JOINT DOD AND DOA ESTIMATION FOR LARGE SCALE MIMO RADAR IN NON-GAUSSIAN NOISE

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ABSTRACT

Traditional methods of target parameter estimation in MIMO radar are carried out under the assumption that the number of observations is much larger than the number of array elements. However, their estimation performance will decline for the MIMO radar with large arrays and insufficient observations. In this paper, we investigate the situation in bistatic MIMO radar that the product of the numbers of the transmit and receive elements and the number of observations grow at the same rate. We propose a robust method for joint direction-of-departure (DOD) and direction-of-arrival (DOA) estimation in non-Gaussian noise environment. The method uses robust M-estimator to form an estimate of the covariance matrix, and then applies random matrix theory (RMT) and polynomial rooting algorithm to receive accurate DOD and DOA estimates for large scale MIMO radar. The simulation results demonstrate the robustness and improvement in accuracy.

***Index Terms*—**MIMO radar, random matrix, non-Gaussian noise, DOA, DOD, robust estimator

1. INTRODUCTION

Recently, joint estimation of direction of departure (DOD) and direction of arrival (DOA) in bistatic multiple-input multiple-output (MIMO) radar [1-3] has drawn considerable attention for target localization. Several two-dimensional (2D) spatial spectrum estimation approaches have been developed [4-9]. In [4], a 2D-Capon method for DOD and DOA estimation has been proposed. In [5], a 2D-MUSIC method has been presented and then a reduced-dimension MUSIC method has been given to reduce its amount of calculation. However, searching through all the 2D space is needed in these methods. In [6][7], the ESPRIT-like methods have been developed exploiting the rotation invariant structure of the transmit and receive arrays, which can avoid peak searching but need pairing between the DOAs and DODs of multiple targets. Furthermore, the combined ESPRIT-MUSIC method [8] with polynomial root finding algorithm [9] has been presented to decompose the 2D angle estimation into double one-dimensional (1D) angle estimation, which allows an automatical pairing of DOAs and DODs, and avoids an exhaustive peak searching.

Despite the fact that the currently proposed methods have improved the performance of DOD and DOA estimation, they work well under the assumption that the number of observations is sufficient and much larger than the number of array elements. Commonly, we observe from the signal model of bistatic MIMO radar that, the number of observations is actually not so large compared to the product of the numbers of the transmit and receive elements, i.e. they both grow at the same rate, which will lead to the performance declination for traditional estimation methods. In addition, the observation noise of MIMO radar often exhibits non-Gaussian characteristics, e.g., heavy-tailed distribution, which will lead to the lack of robustness for traditional methods, since they only work well under Gaussian environment.

The work developed by Mestre et al [10] has considered large array with random matrix theory (RMT) and presented a DOA estimation algorithm with G-estimator. Following this, the work by Romain Couillet et al [11] has proposed a robust G-MUSIC algorithm for DOA estimation. The algorithm starts with the works from Huber [12] on robust M-estimation, and uses the robust estimator of the covariance matrix instead of the sample covariance matrix (SCM), which has shown robustness in non-Gaussian noise.

In this paper, we apply the ideas of [10] and [11] in the bistatic MIMO radar with large scale arrays in which the product of the numbers of the transmit and receiver elements and the number of observations grow at the same rate. We propose a robust method for joint DOD and DOA estimation in non-Gaussian noise environment. In the proposed method, the robust M-estimator is used to form an estimate of the covariance matrix, and then the RMT and polynomial rooting algorithm are exploited to estimate DOD and DOA for large scale MIMO radar. It brings automatical pairing and avoids exhaustive 2D peak searching. Also, it shows robustness when multiple targets own identical DOA but different DODs.

2. SIGNAL MODEL FOR BISTATIC MIMO RADAR

As illustrated in Fig. 1, we consider a bistatic MIMO radar

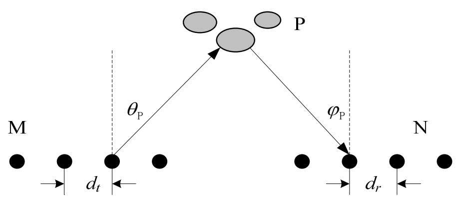

Fig. 1. Bistatic MIMO radar configuration of M transmit array elements and N receive array elements.

system equipped with a uniform linear transmit array with M elements and a uniform linear receive array with N elements. d_t and d_r respectively denote the inter-element spacing at the transmitter and receiver, which are no more than half a wavelength λ. The range of targets is assumed to be much larger than the apertures of the transmit and receive arrays. Assume that the M elements of the transmit array simultaneously send M orthogonal waveforms. The signals are reflected by P targets. For the pth target, $p = 1, 2, \cdots, P$, its angles, say, DOD and DOA, are denoted by θ_p and ϕ_p.

In the lth independant observation, $l = 1, 2, \cdots, L$, the return signals at the receiver array form a matrix denoted as

$$\boldsymbol{X}^{(l)} = \boldsymbol{A}_r(\phi)\boldsymbol{B}^{(l)}\boldsymbol{A}_t^{\mathrm{T}}(\theta)\boldsymbol{S} + \boldsymbol{Z}^{(l)} \quad (1)$$

where $\boldsymbol{S} \in \mathbb{C}^{M\times K}$ denotes the transmitted baseband coded waveform matrix, $\boldsymbol{S} = [\boldsymbol{s}_1, \cdots, \boldsymbol{s}_M]^{\mathrm{T}}$, where $\boldsymbol{s}_m \in \mathbb{C}^{K\times 1}$ is the signal vector of the mth transmit element with length K. Let $\boldsymbol{SS^H} = \boldsymbol{I}$ for M orthogonal transmitted waveforms. $\boldsymbol{B}^{(l)} \in \mathbb{C}^{P\times P}$ denotes the reflected target signal matrix, $\boldsymbol{B}^{(l)} = diag\{\beta_1^{(l)}, \cdots, \beta_p^{(l)}\}$, where $\beta_p^{(l)}$ is complex amplitudes having time-varying characteristics in each observation, which is proportional to the radar cross sections (RCSs) of the pth target. $\boldsymbol{Z}^{(l)} \in \mathbb{C}^{N\times K}$ denotes the noise matrix. $\boldsymbol{A}_t(\theta) \in \mathbb{C}^{M\times P}$ and $\boldsymbol{A}_r(\phi) \in \mathbb{C}^{N\times P}$ respectively denote the transmitter and receiver steering matrices, $\boldsymbol{A}_t(\theta) = [\boldsymbol{a}_t(\theta_1), \cdots, \boldsymbol{a}_t(\theta_P)]$, where $\boldsymbol{a}_t(\theta_p) \in \mathbb{C}^{M\times 1}$ is the pth steering vector of the transmit array, given by

$$\boldsymbol{a}_t(\theta_p) = [1, e^{-j2\pi d_t \sin(\theta_p)/\lambda}, \cdots, e^{-j2\pi(M-1)d_t \sin(\theta_p)/\lambda}]^{\mathrm{T}} \quad (2)$$

and $\boldsymbol{A}_r(\phi) = [\boldsymbol{a}_r(\phi_1), \cdots, \boldsymbol{a}_r(\phi_P)]$, where $\boldsymbol{a}_r(\phi_p) \in \mathbb{C}^{N\times 1}$ denotes the pth steering vectors of the receive array, written as

$$\boldsymbol{a}_r(\phi_p) = [1, e^{-j2\pi d_r \sin(\phi_p)/\lambda}, \cdots, e^{-j2\pi(N-1)d_r \sin(\phi_p)/\lambda}]^{\mathrm{T}} \quad (3)$$

We use $\boldsymbol{S}^{\mathrm{H}}$ as the matched filter matrix. Thus, the output of the matched filter $\tilde{\boldsymbol{X}}^{(l)} \in \mathbb{C}^{N\times M}$ can be written as

$$\tilde{\boldsymbol{X}}^{(l)} = \boldsymbol{X}^{(l)}\boldsymbol{S}^{\mathrm{H}} = \boldsymbol{A}_r(\phi)\boldsymbol{B}^{(l)}\boldsymbol{A}_t^{\mathrm{T}}(\theta) + \boldsymbol{Z}^{(l)}\boldsymbol{S}^{\mathrm{H}} \quad (4)$$

By vectorizing the matrix $\tilde{\boldsymbol{X}}^{(l)}$, i.e. $\boldsymbol{y}^{(l)} = vec(\tilde{\boldsymbol{X}}^{(l)})$, the obtained vector $\boldsymbol{y}^{(l)} \in \mathbb{C}^{MN\times 1}$ can be written as

$$\boldsymbol{y}^{(l)} = \boldsymbol{A}(\theta,\phi)\boldsymbol{b}^{(l)} + \boldsymbol{n}^{(l)} \quad (5)$$

with $\boldsymbol{b}^{(l)} = [\beta_1^{(l)}, \cdots, \beta_P^{(l)}]^{\mathrm{T}}$ being the target amplitude vector. $\boldsymbol{A}(\theta,\phi) \in \mathbb{C}^{MN\times P}$ denotes the total manifold matrix with respect to both the transmit and receive arrays, then

$$\boldsymbol{A}(\theta,\phi) = \boldsymbol{A}_t(\theta)\Diamond\boldsymbol{A}_r(\phi) = [\boldsymbol{a}(\theta_1,\phi_1), \cdots, \boldsymbol{a}(\theta_P,\phi_P)] \quad (6)$$

where $\Diamond$ is the Khatri-Rao product. $\boldsymbol{a}(\theta_p,\phi_p) = \boldsymbol{a}_t(\theta_p)\otimes\boldsymbol{a}_r(\phi_p)$, where $\otimes$ is the Kronecker product. We form a matrix $\boldsymbol{Y} \in \mathbb{C}^{MN\times L}$ by composing L observations from (5),

$$\boldsymbol{Y} = \boldsymbol{A}(\theta,\phi)\boldsymbol{b} + \boldsymbol{N} \quad (7)$$

where $\boldsymbol{Y} = [\boldsymbol{y}^{(1)}, \cdots, \boldsymbol{y}^{(L)}]$, $\boldsymbol{b} = [\boldsymbol{b}^{(1)}, \cdots, \boldsymbol{b}^{(L)}]$, $\boldsymbol{N} = [\boldsymbol{n}^{(1)}, \cdots, \boldsymbol{n}^{(L)}]$.

From the signal model of bistatic MIMO radar in (7), we observe that $\boldsymbol{Y}$ can be regarded as a large dimensional random matrix when $MN \to \infty$, $L \to \infty$, and $MN/L = c$ with c being a constant. Our object is to investigate a robust joint estimation problem in non-Gaussian noise background when L is not so large compared to MN. This condition often holds in MIMO radar with large scale arrays.

3. RANDOM MATRIX-BASED METHOD FOR DOD AND DOA ESTIMATION IN NON-GAUSSIAN NOISE

Subspace-based DOD and DOA estimation methods are based on the empirical covariance matrix of observation signals. For our MIMO radar model, we assume $E[\boldsymbol{Y}] = 0$, $E[\boldsymbol{YY^H}] = \boldsymbol{C}_{MN}$, where $\boldsymbol{C}_{MN}$ is an $MN\times MN$ empirical covariance matrix of $\boldsymbol{Y}$. In traditional methods with large L, the SCM is the maximum likelihood (ML) approximation of $\boldsymbol{C}_{MN}$ for $\boldsymbol{Y}$ Gaussian. However, this may perform very poorly when $\boldsymbol{Y}$ is not Gaussian. In this paper, we use a robust estimator of $\boldsymbol{C}_{MN}$ as the substitution of the SCM estimator to solve the non-Gaussian problem based on Huber' method [12] on robust M-estimation. Here the robust estimator $\hat{\boldsymbol{C}}_{MN}$ is iteratively calculated by

$$\hat{\boldsymbol{C}}_{MN} = \frac{1}{L}\sum_{l=1}^{L} u\left(\frac{1}{MN}(\boldsymbol{y}^{(l)})^{\mathrm{H}}\hat{\boldsymbol{C}}_{MN}^{-1}\boldsymbol{y}^{(l)}\right)\boldsymbol{y}^{(l)}(\boldsymbol{y}^{(l)})^{\mathrm{H}} \quad (8)$$

where $u(\cdot)$ is a non-negative function with specific properties [11]. For any such $u(\cdot)$, $\hat{\boldsymbol{C}}_{MN}$ is a consistent estimate of $\boldsymbol{C}_{MN}$ for MN fixed and $L \to \infty$, which is particularly appropriate as it is the ML estimate of $\boldsymbol{C}_{MN}$ for specific distributions of $\boldsymbol{Y}$ and some specific choices of $u(\cdot)$, such as the family of elliptical distributions [13]. The robust estimator is also used to cope with distributions of $\boldsymbol{Y}$ with heavy tails [14] such as the K-distribution often encountered in adaptive radar processing with impulsive clutter [11][15].

Considering the situation that L is not so large compared to MN, we use the RMT to solve the inadequacy of observations. The method is based on the idea of G-estimator developed in [10]. Denote $\boldsymbol{E}_n \in \mathbb{C}^{MN\times(MN-P)}$ the noise subspace matrix containing in columns the eigenvectors of $\boldsymbol{C}_{MN}$. Also, denote $\hat{\boldsymbol{e}}_m$ the mth eigenvector of $\hat{\boldsymbol{C}}_{MN}$ with respect to the eigenvalue $\hat{\lambda}_m = \hat{\lambda}_m(\hat{\boldsymbol{C}}_{MN})$, $m = 1, 2, \cdots, MN$, where $\hat{\lambda}_1 \le \hat{\lambda}_2 \le \cdots \le \hat{\lambda}_{MN}$ are the ordered eigenvalues. Then, for $MN \to \infty$, $L \to \infty$, $MN / L = c$, and P fixed, we have

$$\left|\gamma(\theta,\varphi) - \hat{\gamma}(\theta,\varphi)\right| \xrightarrow{a.s.} 0 \tag{9}$$

where

$$\gamma(\theta,\varphi) = \boldsymbol{a}^{\boldsymbol{H}}(\theta,\varphi)\boldsymbol{E}_n\boldsymbol{E}_n^{\boldsymbol{H}}\boldsymbol{a}(\theta,\varphi) \tag{10}$$

$$\hat{\gamma}(\theta,\varphi) = \sum_{m=1}^{MN} w(m)\boldsymbol{a}^{\boldsymbol{H}}(\theta,\varphi)\boldsymbol{e}_m\boldsymbol{e}_m^{\boldsymbol{H}}\boldsymbol{a}(\theta,\varphi) \tag{11}$$

with

$$w(m) = \begin{cases} 1 + \sum\limits_{i=MN-P+1}^{MN} \left(\dfrac{\hat{\lambda}_i}{\hat{\lambda}_m - \hat{\lambda}_i} - \dfrac{\hat{\mu}_i}{\hat{\lambda}_m - \hat{\mu}_i} \right), & m \le MN - P \\ -\sum\limits_{i=1}^{MN-P} \left(\dfrac{\hat{\lambda}_i}{\hat{\lambda}_m - \hat{\lambda}_i} - \dfrac{\hat{\mu}_i}{\hat{\lambda}_m - \hat{\mu}_i} \right), & m > MN - P \end{cases} \tag{12}$$

where $\hat{\mu}_1 \le \hat{\mu}_2 \le \cdots \le \hat{\mu}_{MN}$ are the eigenvalues of $diag(\hat{\boldsymbol{\lambda}}) - \frac{1}{L}\sqrt{\hat{\boldsymbol{\lambda}}}\sqrt{\hat{\boldsymbol{\lambda}}}^{\boldsymbol{T}}$, with $\hat{\boldsymbol{\lambda}} = (\hat{\lambda}_1, \hat{\lambda}_2, \cdots, \hat{\lambda}_{MN})^{\mathrm{T}}$.

Simlarly to conventional MUSIC algorithm exploiting the orthogonality of the steering vector matrix and the noise subspace, we estimate (θ,ϕ) by constructing the following peak searching function:

$$P(\theta,\phi) = \frac{1}{\boldsymbol{a}(\theta,\phi)^{\mathrm{H}} \left(\sum\limits_{m=1}^{MN} w(m)\hat{\boldsymbol{e}}_m\hat{\boldsymbol{e}}_m^{\mathrm{H}} \right) \boldsymbol{a}(\theta,\phi)} \tag{13}$$

To avoid searching through all the 2D space, we use the polynomial root algorithm. Denote $\mathrm{z}_r = e^{-j2\pi d_r \sin(\phi)/\lambda}$, $\mathrm{z}_t = e^{-j2\pi d_t \sin(\theta)/\lambda}$ and rewrite the steering vectors as

$$\boldsymbol{a}_r(z_r) = \left[1, z_r, z_r^2, \ldots, z_r^{N-1}\right]^T \tag{14}$$

$$\boldsymbol{a}_t(z_t) = \left[1, z_t, z_t^2, \ldots, z_t^{M-1}\right]^T \tag{15}$$

Since $\boldsymbol{a}(\theta,\phi) = \boldsymbol{a}_t(\theta) \otimes \boldsymbol{a}_r(\phi)$, we have

$$\boldsymbol{a}(z_r,z_t) = \left[\boldsymbol{a}_r(z_r)^T, z_t\boldsymbol{a}_r(z_r)^T, z_t^2\boldsymbol{a}_r(z_r)^T, \ldots, z_t^{M-1}\boldsymbol{a}_r(z_r)^T\right]^T \tag{16}$$

From (13) and (16),

$$\boldsymbol{a}(z_r, z_t)^H \left(\sum_{\mathrm{m}=1}^{MN} w(m)\hat{\boldsymbol{e}}_m\hat{\boldsymbol{e}}_m^{\mathrm{H}} \right) \boldsymbol{a}(z_r, z_t) = 0 \tag{17}$$

Let

$$\boldsymbol{\Pi}_n = \sum_{\mathrm{m}=1}^{MN} w(m)\hat{\boldsymbol{e}}_m\hat{\boldsymbol{e}}_m^{\mathrm{H}} \tag{18}$$

Then

$$\boldsymbol{a}(z_r^{-1}, z_t^{-1})^T \boldsymbol{\Pi}_n \boldsymbol{a}(z_r, z_t) = 0 \tag{19}$$

Divide $\boldsymbol{\Pi}_n \in \mathbb{C}^{MN \times MN}$ into

$$\boldsymbol{\Pi}_n = \begin{bmatrix} \boldsymbol{\Pi}_{11} & \cdots & \boldsymbol{\Pi}_{1M} \\ \vdots & \ddots & \vdots \\ \boldsymbol{\Pi}_{M1} & \cdots & \boldsymbol{\Pi}_{MM} \end{bmatrix}, \quad \boldsymbol{\Pi}_{ij|i,j=1,\ldots,M} \in C^{N \times N} \tag{20}$$

Rewrite (19) as

$$\boldsymbol{a}_r(z_r^{-1})^T \left[\sum_{i,j=1}^{M} z_t^{j-i} \boldsymbol{\Pi}_{ij} \right] \boldsymbol{a}_r(z_r) = 0 \tag{21}$$

By finding the roots of the polynomial function in (21), the estimation of θ and ϕ can be obtained.

For DOD estimation, z_t satisfies [9]

$$D(z_t) = \det\left[\sum_{j,i=1}^{M} z_t^{j-i} \boldsymbol{\Pi}_{ij} \right] = 0 \tag{22}$$

where det (.) denotes the determinant of a matrix. Therefore, the DOD can be estimated by obtaining the P roots inside and closest to the unitary circle of the polynomial in (22), i.e.

$$\hat{\theta}_p = \arcsin\left(\frac{\lambda}{2\pi d_t} \arg(\breve{z}_t^{(p)}) \right) \tag{23}$$

where $\breve{z}_t^{(p)}$ is the pth roots of the equation in (22).

For DOA estimation, substituting $\breve{z}_t^{(p)}$ into (21), we have

$$\boldsymbol{a}_r(z_r^{-1})^T \left(\sum_{j,i=1}^{M} (\breve{z}_t^{(p)})^{j-i} \boldsymbol{\Pi}_{ij} \right) \boldsymbol{a}_r(z_r) = 0 \tag{24}$$

Using again the root finding technique respectively for $p = 1, \ldots, P$, the DOA can be determined by calculating the root closest to the unit circle of the obtained polynomial in (24), i.e.

$$\hat{\phi}_p = \arcsin\left(\frac{\lambda}{2\pi d_r} \arg(\breve{z}_r^{(p)}) \right) \tag{25}$$

where $\breve{\mathrm{z}}_r^{(p)}$ is the root of the equation in (24) with respect to the pth target.

4. SIMULATION RESULTS

In this section, we present the simulation results to illustrate the performance of the proposed algorithms. The bistatic MIMO radar is composed of M=8 and N=8 transmit and receive elements, respectively. All the elements are spaced by a half wavelength. The function $u(x)$ in (8) is given as $u(x) = (1+v)/(x+v)$ with $v = 0.5$. The snapshots is L=80. We observe that MN=64 is close to L. The Monte-Carlo iterations is 200. Assume that the noise matrix $\boldsymbol{N}$ is independent zero-mean unit variance entries with Student-t distribution [16] with degrees of freedom 2.5, and SNR=10dB. We show the robust DOD and DOA estimation results in non-Gaussian noise environment.

Example 1: Firstly, we assume that $\boldsymbol{N}$ is independent zero-mean unit variance entries with Gaussian distribution. Here, P=4 targets are located at the angles $(\theta,\phi) =$

$(10^\circ,20^\circ),(50^\circ,30^\circ)$, $(40^\circ,50^\circ),(80^\circ,70^\circ)$. The result of the proposed algorithm in Gaussian noise environment is shown in Fig. 2. Secondly, assume that $\boldsymbol{N}$ is independent zero-mean unit variance entries with Student-t distribution. Four targets are located at $(\theta,\varphi)=(10^\circ,20^\circ),(70^\circ,40^\circ),(80^\circ,60^\circ),(50^\circ,80^\circ)$. The result of the proposed algorithm in non-Gaussian noise is shown in Fig. 3.

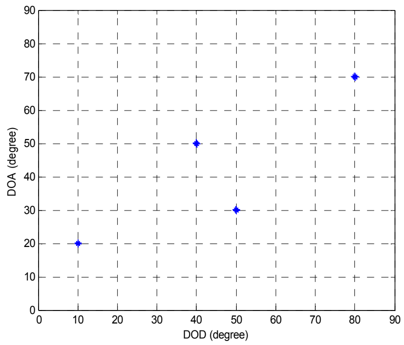

Fig. 2. The result of robust DOD and DOA estimation under Gaussian noise. *P*=4, *M*=*N*=8, *L*=80, *SNR*=10dB.

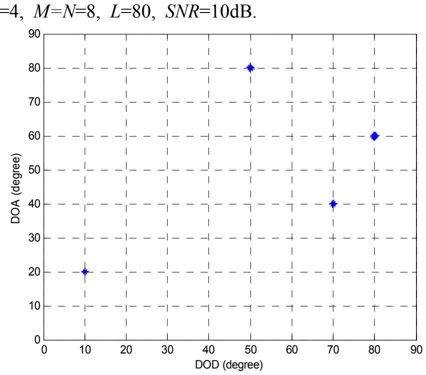

Fig. 3. The result of robust DOD and DOA estimation under Student-t distribution noise. *P*=4, *M*=*N*=8, *L*=80, *SNR*=10dB.

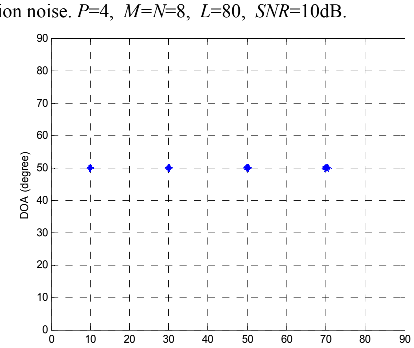

Fig. 4. Robust DOD and DOA estimation when two targets have the same DOA but different DODs. *P*=4, *M*=*N*=8, *L*=80, *SNR*=10dB, under Student-t distribution noise.

From Fig. 2 and Fig. 3 we can observe that the target angles are well localized and they are automatically paired. The proposed DOD and DOA estimation algorithm is robust and suitable for both Gaussion and non-Gaussion noise environment. Also, the method is applicable in inadequate snapshots *L*=80.

Example 2: The example investigates the effectiveness of the proposed method when multiple targets have the identical DOA but different DODs. Four targets locate at $(\theta,\varphi)=(10^\circ,50^\circ),(30^\circ,50^\circ),(50^\circ,50^\circ),(70^\circ,50^\circ)$. The noise matrix is independent zero-mean unit variance entries with Student-t distribution. The obtained result is shown in Fig. 4.

Example 3: The performance of our method is compared with that of the 2D-MUSIC algorithm [5] and the ESPRIT method [6] in non-Gaussian environment. Two closely spaced targets locate at $(\theta,\varphi)=\left(30^\circ,40^\circ\right),\left(27^\circ,45^\circ\right)$. The simulation results in Fig. 5 present the root mean square error (RMSE) versus SNR. We observe that the proposed algorithm has better performance on precision compared with the other two methods under non-Gaussian noise and for *MN* not small compared to *L*.

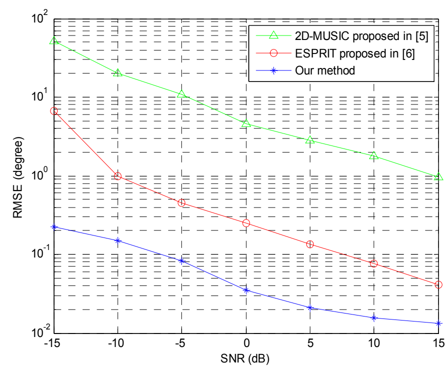

Fig. 5. RMSE of DOA and DOD estimation by 2D-MUSIC, ESPRIT and our method under Student-t distribution noise. *P*=2, *N*=*M*=8, *L*=80.

5. CONCLUSION

Aiming at large scale MIMO radar system, a novel random matrix-based method for joint DOD and DOA estimation in non-Gaussian noise is proposed. Compared with traditional algorithms, the proposed algorithm has several advantages: When the observations is close to the product of the numbers of the transmit and receive array elements, the proposed algorithm performs better than other measures. Also, it performs robustness when the noise in the radar returns are characterized by non-Gaussian distribution. By using the 2D polynomial rooting, the algorithm does not require a time-consuming search in 2D space. It improves the performance of DOD and DOA estimation in bistatic MIMO radarr with large arrays and non-Gaussian noise.

6. ACKNOWLEDGEMENT

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