Tensor based angle estimation scheme for strictly noncircular sources in bistatic MIMO radar

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Abstract. In this paper, joint direction of departure (DOD) and direction of arrival (DOA) estimation for strictly noncircular sources in multiple-input multiple-output (MIMO) radar is dealt with by a novel tensor based subspace method. The proposed method firstly formulates a novel augmented tensor for capturing both the noncircularity and inherent multidimensional structure of strictly noncircular signals, and then a tensor based signal subspace is constructed by utilizing the high-order singular value decomposition (HOSVD). Finally, the DODs and DOAs are achieved by calculating the rotational invariance factors corresponding to the augmented steering matrix. The proposed method provides better angle estimation performance than the existing subspace based algorithms, especially in the case of low SNR and a small number of snapshots. In addition, the DODs and DOAs are paired automatically. The effectiveness and advantages of the proposed method are demonstrated via simulation results.

1. Introduction
Following the concept of multiple-input multiple-output (MIMO) communications, MIMO radars have been widely investigated in recent years due to obtainable spatial diversity gain and waveform diversity [1-3]. The MIMO radar architecture is of two kinds: statistical MIMO radar and collocated MIMO radar. Both the transmit and receive antennas or at least one of them are widely spaced in statistical MIMO radar, which can achieve the spatial diversity gain for solving the problem of radar cross section (RCS) fluctuations [2]. The colocated MIMO radar is equipped with closely spaced transmit and receive antennas to provide more degree of freedom and higher spatial resolution for detection and angle finding by using the waveform diversity [3]. The bistatic MIMO radar belongs to this category, but the transmit and receive arrays are far apart. In the last few years, angle estimation, including direction of departure (DOD) and direction of arrival (DOA), has been of great research interest in MIMO radar. In most studies, the subspace based algorithms, including multiple signal classification (MUSIC) [4] and estimation method of signal parameter via rotational invariance techniques (ESPRIT) [5], have been proposed for angle estimation due to their conventional implementation and suboptimal performance [4-7], but these methods are based on a circular signal model only without considering other signal structures.

For angle estimation, the accuracy is the key issue in MIMO radar. By considering the inherent multidimensional structure of signals in MIMO radar, the high-order singular value decomposition (HOSVD) technique is utilized to achieve a more accurate subspace, which results in better angle
estimation compared with the conventional subspace based algorithms [8-10]. One the other hand, the strictly noncircular signals, such as binary phase shift keying (BPSK) and M-ary amplitude shift keying (MASK), have been widely used in communication and radar systems for aperture extension [11,12]. For MIMO radar, a conjugate ESPRIT (C-ESPRIT) algorithm is proposed for DOD and DOA estimation via utilizing the noncircularity of signals to achieve better angle estimation performance than the traditional subspace based methods [13]. In addition, a real-valued version of C-ESPRIT, known as conjugate unitary ESPRIT (CU-ESPRIT) [14], is investigated to estimate DOD and DOA with lower computational complexity. According to the analysis above, the noncircularity and inherent multi-dimensional structure of strictly noncircular signals are utilized separately. To the best of our knowledge, there have not been reported works in the literatures about exploiting both noncircularity and inherent multidimensional structure to achieve high resolution angle estimation in MIMO radar.

In this paper, we propose a tensor based angle estimation scheme for strictly noncircular sources in MIMO radar. Firstly, the proposed method formulates a novel augmented tensor for capturing both the noncircularity and inherent multi-dimensional structure of strictly noncircular signals. Then the HOSVD technique is applied to construct the tensor based signal subspace. Finally, the DODs and DOAs are estimated by utilizing the rotational invariance technique. Due to the exploitation of inherent multidimensional structure and enlarged array aperture, the proposed method provides superior performance than the existing subspace based algorithms, especially in the case of low SNR and a small number of snapshots. In addition, the DODs and DOAs are paired automatically.

Notation: $(\cdot)^H$, $(\cdot)^T$, $(\cdot)^{-1}$ and $(\cdot)^*$ denote conjugate-transpose, transpose, inverse, conjugate, respectively. $\otimes$ and $\odot$ denote the Kronecker product and Khatri-Rao product. $\text{diag}(\cdot)$ is the diagonalization operation, and vec$(\cdot)$ denotes the vectorization operation. $\text{arg}(\cdot)$ denotes the phase of $\gamma$. $I_K$ denotes a $K\times K$ dimensional unit matrix, and $\Gamma_K$ represents a matrix with ones on its anti-diagonal and zeros elsewhere.

2. TENSOR BASICS DATA MODEL

2.1. Tensor Basics

In order to describe the tensor based data model and derive the algorithm conveniently, several basic tensor operations are introduced as follows [9, 15].

Mode-$n$ matrix unfolding: The mode-$n$ matrix unfolding of a tensor $\chi \in \mathbb{C}^{I_1 \times I_2 \times \cdots \times I_N}$ is denoted by $[\chi]_{(n)} = (i_{1}, i_{2}, \ldots, i_{n}) dh$ element of $\chi$ maps to the $(i_{n}, j)th$ element of $[\chi]_n$, where $j = 1 + \Sigma_{k=1,k\ne{n}}^{K} (i_{k} - 1)J_k$ with $J_k = \Pi_{m=1,m\ne{n}}^{K} I_m$.

Mode-$n$ tensor-matrix product: The Mode-$n$ product of $\chi \in \mathbb{C}^{I_1 \times I_2 \times \cdots \times I_N}$ with a matrix $A \in \mathbb{C}^{I_n \times I}$ is defined as $\gamma = \chi \times_n A$, where $\gamma \in \mathbb{C}^{I_1 \times I_2 \times \cdots \times I_{n-1} \times I_n \times I_{n+1} \times \cdots \times I_N}$ and

$$[\gamma]_{1 \cdots i_n \cdots i_{n+1} \cdots i_N} = \sum_{i_1=1}^{I_1} \cdots \sum_{i_{n-1}=1}^{I_{n-1}} [\chi]_{1 \cdots i_1 \cdots i_{n-1} \cdots i_N} (\ast)_{i_n} \ast \cdots \ast (\ast)_{i_{n+1}}$$

The properties of the mode product: The properties of the mode product used in the following derivation are given as

$$\chi \times_n A \times_m B = \chi \times_n A \times_m B, m \neq n; \quad \chi \times_n A \times_m B = \chi \times_n (AB)$$

$$[\chi \times_1 A_1 \times_2 A_2 \cdots \times_n A_n]_{(n)} = A_n [\chi]_{(n)} \otimes \cdots \otimes A_{n+1} \otimes \cdots \otimes A_1^T$$

Mode-$n$ concatenation of two tensors: The mode-$n$ concatenation of tensors $\chi \in \mathbb{C}^{I_1 \times I_2 \times \cdots \times I_N}$ and $\gamma \in \mathbb{C}^{I_1 \times I_2 \times \cdots \times I_N}$ is denoted as $F = [\chi \perp_n \gamma]$, where $F \in \mathbb{C}^{I_1 \times I_2 \times \cdots \times 2 I_N \times I_N}$. 

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2.2. Tensor Based Data Model

Consider a narrowband bistatic MIMO radar consisting of an $M$-element transmit array and an $N$-element receive array, and both of which are half-wavelength spaced uniform linear arrays (ULAs). Because transmit and receive arrays are far from each other in bistatic MIMO radar, the directions of a source with respect to the transmit array normal and receive array normal are denoted as DOD $\phi$ and DOA $\theta$, respectively. At the transmit array, $M$ elements emit $M$ mutual orthogonal BPSK modulated signals, i.e., strictly noncircular signals, with identical bandwidth and centre frequency. Assume that there are $P$ uncorrelated sources in the far filed of the transmit and receive arrays, and the location of the $p$th source is denoted as $(\phi_p, \theta_p)$. The reflected signals are collected by the receive antennas snapshot by snapshot and dealt with matched filters formed by the transmitted orthogonal waveforms. Then the output of matched filters can be written as [8, 13, 14]

$$X(t_l) \in \mathbb{C}^{N \times M} \sum_{l=1}^{L} X(t_l) = A_1 \sum_{l=1}^{L} A_2^T + N(t_l), \quad l = 1, 2, ..., L$$

where $X(t_l) \in \mathbb{C}^{N \times M}$ is the received data at the $l$th snapshots, $A_1 = \{a_1(\theta_1), a_1(\theta_2), ..., a_1(\theta_P)\} \in \mathbb{C}^{N \times P}$ is the receive steering matrix consisting of receive steering $a_1(\theta_p) = [\exp(j\pi \sin \theta_1), ..., \exp(j\pi(N-1) \sin \theta_2)]^T$, and $A_2 = [a_2(\theta_1), a_2(\theta_2), ..., a_2(\theta_P)] \in \mathbb{C}^{N \times P}$ is the transmit steering matrix consisting of the transmit steering vector $a_2(\phi_p) = [\exp(j\pi \sin \phi_1), ..., \exp(j\pi(M-1) \sin \phi_2)]^T$. $\sum(t_l) = \text{diag}(s(t_l)) \in \mathbb{C}^{P \times P}$ is the strictly noncircular signal data with $s(t_l) = [s_1(t_l), s_2(t_l), ..., s_P(t_l)]^T$ at the $l$th snapshots, and the noncircular signal vector $s(t_l)$ satisfies with $s(t_l) = \Delta s(t_l)$ where $\Delta = diag([\exp(j\phi_1), ..., \exp(j\phi_P)])$ with the arbitrary phases $\phi_p (p = 1, 2, ..., P)$ is assumed to be different for each source, and $s_p(t_l) = \bar{s}_p(t_l).N(t_l) \in \mathbb{C}^{N \times M}$ is the additional Gaussian white noise matrix. Based on the concept of tensor, the received data $X(t_l)(l = 1, 2, ..., L)$ can be seen as different slices of a third-order tensor along the direction of snapshot (the third-dimension). By collecting $L$ snapshots, a third-order tensor data $\chi \in \mathbb{C}^{N \times M \times L}$ is formed as

$$\chi_{l} = X(t_l), l = 1, 2, ..., L$$

where $\chi_{l}$ is the $l$th slice of the tensor along the third-dimension. According to the definition of Mode-$n$ matrix unfolding, the relationship between the tensor based data model and matrix based data model is expressed as

$$\chi_{l}^{(3)} = AS + N = A\Delta S + N$$

where $A = A_1 \odot A_2$ is the transmit-receive steering matrix, $S = [s_1(t_l), s_2(t_l), \ldots, s_P(t_l)] \in \mathbb{R}^{P \times L}$ is the signal matrix, $\Delta S = [\bar{s}_1(t_l), \bar{s}_2(t_l), \ldots, \bar{s}_P(t_l)] \in \mathbb{R}^{P \times L}$ satisfies $S = \Delta S$, $N = [\text{vec}(N(t_1)), \text{vec}(N(t_2)), \ldots, \text{vec}(N(t_L))] \in \mathbb{C}^{MN \times L}$ is the noise matrix.

In the subspace based algorithms [13,14], although the noncircularity of signals is used to extend the data matrix for improving the performance, the inherent multidimensional structure is ignored. On the other hand, the algorithms in [8-10] are based on the tensor model in Eq.(4), but the noncircularity of signals are not utilized. In the following section, a novel augmented tensor is formulated for achieving more accurate angle estimation by capturing the noncircularity and inherent multidimensional structure of the signals simultaneously.

3. TENSOR BASED ANGLE ESTIMATION SCHEME

3.1. Tensor Augmentation and Subspace Estimation
In order to capture the noncircularity of signals in the tensor model, a novel augmented tensor is formulated as

$$y = \left[ x_{\perp}, (x^* \otimes \Gamma_N \otimes \Gamma_M) \right]$$

(6)

Then according to the definition \textbf{Mode-}\(n\) \textbf{matrix unfolding}, the mode-3 matrix unfolding of

$$[y]_{3,\times}^T = [(A_1^1) \otimes \overline{A}_r] \times S_r + \overline{N}$$

(7)

where \(\overline{A}_r = [(A_1^1)^T, (A_2^2)^T] \in \mathbb{C}^{2MN \times P}\) denotes the extended steering matrix, where \(A_1^1 = A_r \Delta\) and \(A_2^2 = A_r \Delta D_1 D_2\), with \(D_1 = \text{diag}([\exp(-j\pi(M-1)\sin \phi_1), \exp(-j\pi(M-1)\sin \phi_2), \ldots, \exp(-j\pi(M-1)\sin \phi_p])]\) and \(D_2 = \text{diag}([\exp(-j\pi(M-1)\sin \theta_1), \exp(-j\pi(M-1)\sin \theta_2), \ldots, \exp(-j\pi(M-1)\sin \theta_s])]\), \(\overline{N}\) is the rearranged noise matrix. It can be seen from Eq.(7) that the available array aperture is twice of the model in Eq.(4) and (5), thus, it is indicated that the augmented tensor \(y\) achieves both the noncircularity and inherent multidimensional structure of signals for improving the estimation performance. The HOSVD method is applied to the augmented tensor \(y\), we have

$$y = \varsigma \times E_1 \times E_2 \times E_3$$

(8)

where \(E_1 \in \mathbb{C}^{2N \times 1}, E_2 \in \mathbb{C}^{M \times N}\) and \(E_3 \in \mathbb{C}^{L \times M}\) are unitary matrices, which are composed of the left singular of the mode-\(n\) of matrix unfolding of \(y\) as

$$[y]_{3,\times} = E_m \Lambda_n V_N$$

respectively. \(\varsigma \in \mathbb{C}^{2MN \times 2L}\) represents the core tensor. Because there are \(P\) sources, \(y\) is rank-\(P\) tensor. Then a subspace tensor is achieved by using the truncated HOSVD of \(y\), which is shown as

$$y_s = \varsigma_x X_1 \times E_2 \times E_3$$

(9)

where \(E_m \in \mathbb{C}^{2N \times 2L}\) is composed of the column vectors of \(E_s\) corresponding to the largest \(P\) singular values, and \(\varsigma_s = y \times E_s^H \times E_s^H \times E_s^H\) denotes the signal component of \(\varsigma_s\). Then according to the definition of \textbf{Mode-}\(n\) \textbf{tensor-matrix product}, substituting \(\varsigma_s\) into Eq.(9) yields

$$y_s = y \times (E_s^H \otimes E_{s_1}^H) \times (E_{s_2}^H \otimes E_{s_3}^H)$$

(10)

Then the tensor based signal subspace is given by using the mode-3 matrix unfolding of \(y_s\), and according to the \textbf{properties of the mode product}, the tensor based signal subspace is shown as

$$\overline{U}_s = [y]_{3,\times}^T \times (E_s^H \otimes E_{s_1}^H)\times E_{s_3}^H$$

(11)

After using some simplification in [8, 9], the tensor based signal subspace is written as

$$\overline{U}_s = (E_s^H \otimes E_{s_1}^H \otimes E_{s_2}^H)\times U_s$$

(12)

where \(U_s\) is the signal subspace of \([y]_{3,\times}\), which can be estimated by truncating SVD of \([y]_{3,\times}\) as

$$[y]_{3,\times} = U_s \Lambda_s V_s$$

According to Eq.(12), it is indicated that the \(U_s\) and \(U_s\) span the same subspace, which means that the tensor based signal subspace \(\overline{U}_s\) and augmented steering matrix \(\overline{A} = A_r \otimes \overline{A}\), also span the same subspace. Thus, there exists a nonsingular matrix \(T\) satisfied with \(\overline{U}_s = \overline{A} T\), and the DODs and DOAs can be estimated from this tensor based signal subspace.

### 3.2. Joint DOD and DOA Estimation

Noting that \(A_r\) has Vandermonde structure and according to the configuration of the augmented steering matrix, there exists the following rotational invariance factor

$$\Pi_s \overline{A} = \Pi_s \overline{\Phi}_s$$

(13)
where $\Phi_i = \text{diag}([\exp(j\pi\sin\phi_p), \exp(j\pi\sin\phi_p), \ldots, \exp(j\pi\sin\phi_p)])$ is rotational invariance factor matrix contains the desired information of DOAs. $\Pi_i = J \otimes I_{nx}$ and $\Pi_z = J_z \otimes I_{nx}$ are selection matrices with $J_i = [I_{M-1}, O_{(M-1)x1}]$ and $J_z = [O_{(M-1)x1}, I_{M-1}]$, respectively. Simultaneously, both $A_i$ and $A_z$ have the Vandermonde-like structures in $\tilde{A}$. There for there exists another rotational invariance factor corresponding to the augmented steering matrix, which is expressed as

$$\Pi_i \tilde{A} = \Pi_z \tilde{A} \Phi',$$

where $\Phi', = \text{diag}([\exp(j\pi\sin\theta_1), \exp(j\pi\sin\theta_2), \ldots, \exp(j\pi\sin\theta_P)])$ contains the desired information of DODs. $\Pi_i = I_{nx} \otimes J_z$ and $\Pi_z = I_{nx} \otimes J_z$ are the selection matrices with $J_z = [I_{N-1}, O_{(N-1)x1}]$ and $J_z = [O_{(N-1)x1}, I_{N-1}]$,respectively. Utilizing the relationship between the augmented steering matrix and tensor based signal subspace shown as $\tilde{U}_s = \tilde{A} \Psi$, we achieve the following rotational invariance property

$$\Pi_i \tilde{U}_s = \Pi_z \tilde{U}_s \Psi_i' \quad \Pi_z \tilde{U}_s = \Pi_z \tilde{U}_s \Psi_z',$$

where $\Psi_i' = T \Phi_i T^{-1}$ and $\Psi_z' = T \Phi_z T^{-1}$. The least squares (LS) or the total least squares (TLS) technique is applied to Eq.(15) for estimating $\Psi_i'$ and $\Psi_z'$. The diagonal elements of $\Phi_i$ is composed of the eigenvalues of the EVD of $\Psi_i'$. Since $\Psi_i'$ and $\Psi_z'$ have the same eigenvalue vectors, the diagonal matrix $\Phi_i'$ is estimated as $\Phi_i' = T^{-1} \Psi_i' T$. Because the diagonal elements of $\Phi_i$ and $\Phi_z$ in the same position corresponding to the same source, the DODs and DODs are paired automatically. Finally, the DODs and DOAs are derived as

$$\hat{\phi}_p = \arcsin[\text{arg}(u_p) / \pi] \quad \text{and} \quad \hat{\theta}_p = \arcsin[\text{arg}(v_p) / \pi]$$

Where $u_p$ and $v_p$ are the $p$ th diagonal elements of $\Phi_i$ and $\Phi_z$, respectively.

**Remark:** It should be highlighted that the tensor based signal subspace $\tilde{U}_s$ is achieved by utilizing the noncircularity and the inherent multidimensional structure of strictly noncircular signals, which results in more accurate signal subspace and better estimation performance. On the other hand, the proposed method requires HOSVD of the augmented $\gamma$, therefore its computational complexity is higher than the existing subspace based algorithms. When $L \geq 2MN$, the covariance tensor approach in [8] can be used to estimate the signal subspace $\tilde{U}_s$ for reducing the computational complexity.

### 4. SIMULATION RESULTS

In this section, some simulation results are presented to demonstrate the performance of the proposed algorithm. The ESPRIT algorithm [5], C-ESPRIT [13] and multi-SVD algorithm [8] are used to compared with the proposed method. In the following simulations, the bistatic MIMO radar is configured with $M = 4$ transmit antennas and $N = 5$ receive antennas, and $M$ transmit antennas emit $M$ mutual orthogonal BPSK modulated waveforms. Assume that there are $P = 3$ uncorrelated sources located at the angles $(\phi_1, \theta_1) = (-8^\circ, 8^\circ)$, $(\phi_2, \theta_2) = (0^\circ, 0^\circ)$, $(\phi_3, \theta_3) = (10^\circ, -10^\circ)$. The root mean square error (RMSE) is used to evaluate the algorithms, which is defined as

$$\text{RMSE} = \sqrt{\frac{1}{1000} \sum_{p=1}^{P} \sum_{i=1}^{500} [(\hat{\phi}_p - \phi_p)^2 + (\hat{\theta}_p - \theta_p)^2]}$$

where $\hat{\phi}_p$ and $\hat{\theta}_p$ are the estimated value of DOD $\phi_p$ and DOA $\theta_p$ for the $i$th Monte Carlo trial, respectively, and the total number of Monte Carlo trials is 500.
Fig. 1. RMSE versus SNR with different algorithms.

Fig. 1 depicts the RMSE versus SNR with different algorithms, where the number of snapshots is 50. From Fig.1, it can be seen that the multi-SVD algorithm provides better performance than ESPRIT algorithm due to the exploitation of inherent multidimensional structure of the signals, which is consistent with the results in [8]. On the other hand, the C-ESPRIT algorithm has better performance than multi-SVD algorithm when the SNR is high enough, which indicates that enlarging the virtual aperture is a more effective way to improve the angle estimation performance. Because the proposed method captures the noncircularity and multidimensional structure of signals simultaneously, it achieves the best performance compared with other algorithms.
Fig. 2 shows the RMSE versus the number of snapshots with different algorithms, where the SNR is 0dB. As seen in Fig.2, the performances of all methods are improved with the increasing number of snapshots. In addition, the proposed method provides better performance than ESPRIT, C-ESPRIT and multi-SVD algorithms with a small number of snapshots, but has similar performance to them when the number of snapshots is large enough.

Fig.3 shows the probability of successful detection versus SNR with different algorithms, where the number of snapshots is 50. Successful detection requires that the absolute errors of all the estimated angles are smaller than $\min[(\theta_p - \theta_{p})_{\text{min}}, (\theta_p - \theta_{\text{p}})_{\text{max}}]$. It is clearly shown that the proposed method provides higher successful detection than ESPRIT, C-ESPRIT and multi-SVD algorithms. This is because of the advantages mentioned above in the proposed method.

5. Conclusion
In this paper, we have proposed a tensor based angle estimation scheme for strictly noncircular signals in MIMO radar. The proposed method can capture both noncircularity and multidimensional structure of signals via formulating a novel augmented tensor. Then utilizing HOSVD technique, the tensor based signal subspace is constructed, and the rotational invariance factors are calculated for joint DOD and DOA estimation. Simulation results have verified that the proposed method has better angle estimation than the existing subspace based methods, especially in the case of low SNR and a small number of snapshots.

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