Classification and Localization of Mixed Sources Using Uniform Circular Array under Unknown Mutual Coupling

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Abstract. *In this paper, the authors propose an effective classification and localization algorithm of mixed far-field and near-field sources using a uniform circular array under an unknown mutual coupling. In practice, the assumption of an ideal receiving sensor array is rarely satisfied. The effects of unknown mutual coupling would degrade the performance of most high resolution algorithms. Firstly, according to rank reduction type method, the direction of arrival of far-field sources is estimated directly without mutual coupling elimination. Then, these estimates are adopted to reconstruct the mutual coupling matrix. Finally, both direction and range parameters of near-field sources are obtained through MUSIC search after mutual coupling effects and far-field components elimination. The proposed algorithm only requires the second order cumulant and any three dimensional spectrum search is circumvented. Some simulation results would prove that the proposed algorithm can reduce more than eighty percent estimating error of mixed sources localization compared to those algorithms without mutual coupling compensation.*

Keywords

Uniform circular array, direction of arrival, far-field, near-field, mutual coupling

1. Introduction

Source localization using the sensor array techniques has received considerable attention over the past decades. For far-field (FF) sources whose wave fronts is plane wave, only the direction of arrival (DOA) parameter is needed to be estimated. A number of high resolution algorithms have been proposed to deal with the DOA estimation problem of FF sources in the past decades, such as the estimation of signal parameters via rotational invariance technique (ESPRIT) [1], [2], multiple signal classification (MUSIC) method [3], [4], and so on. All aforementioned algorithms generally work based on the ideal receiving sensor array assumption without steering vectors mismatch, such as the unknown mutual coupling [5] and the spherical wave front effect [6].

However, in many interesting applications, some incident sources may locate in the Fresnel Region defined as the near-field (NF) of the array, and these sources would be defined as NF sources [7]. For NF sources, both the DOA and range parameters are required to be estimated since the plane wave front assumption is no longer valid. Therefore, the traditional FF sources' DOA estimation algorithms would have inefficient results for NF sources' parameters estimation. Various algorithms have been developed in the past decades for the NF sources' localization, such as the reduced rank (RERA) type methods [8–11], the covariance approximation (CA) type algorithms [12], [13], the two dimensional (2D) MUSIC algorithm [5], and the weighted linear prediction method [14]. Although all the aforementioned algorithms focus on the pure FF or NF sources scenario [15], it is more realistic in many applications that FF and NF sources coexist, such as electronic surveillance, seismic exploration and speaker localization using microphone arrays. In the mixed NF and FF sources scenario, the above mentioned algorithms may fail to deal with the mixed sources problem.

Recently, a number of algorithms have been developed to deal with the problem of mixed sources classification and localization [16–22]. A two-stage MUSIC (TSMUSIC) algorithm has been proposed to solve the mixed sources issue by Liang, which has used the fourth order cumulant (FOC) technique [16]. Consequently, TSMUSIC constructs a special FOC matrix to eliminate the range parameter in the steering vectors with high computational cost. In [17], an oblique projection MUSIC (OPMUSIC) algorithm based on the second order cumulant (SOC) has been presented by Zhi. Although this algorithm has low computational complexity, it has greater loss of array aperture. According to the generalized ESPRIT algorithm in [11], a GESPRIT-like algorithm has been presented by Liu to fully utilize the array aperture and it provided a reasonable simulation result [21].

As well known, the performance of all abovementioned algorithms would obviously degrade without array calibration. In order to deal with the problem, lots of mutual coupling modeling methods and DOA estimation algorithms of FF sources have been presented [23–28]. In [23] and [24], various middle sub-array methods are presented to estimate DOAs by setting auxiliary sensors, without calibration. However, these methods suffer from a great aperture loss. In [25], a method based on FOC has been presented to deal with the problem of aperture loss. Another popular type of methods against mutual coupling effect is based on the RERA type algorithms [25–29]. These methods take full advantage of the array aperture. Thus, they are expected to provide a better estimation performance.

It is worth noting that all the aforementioned high resolution methods are all aimed at the estimation of elevation angle and range. For three dimensional (3D) problems (azimuth angle, elevation angle and range), these methods may fail in mix sources localization. Uniform circular array (UCA) is preferable over uniform linear array because of its 360° azimuthal coverage, additional elevation angle information and almost unchanged directional pattern for estimating the mixed sources [30]. In [31], a TSMUSIC-like method using UCA is proposed, which is based on SOC. In [32], a covariance differencing like (CD-like) algorithm is presented to reduce computational complexity. However, both of the two algorithms deal with the problem without the mutual coupling compensation.

In this paper, an effective algorithm based on two-stage RERA is presented to deal with sources classification and localization with the effect of unknown mutual coupling. According to the symmetric Toeplitz property of the mutual coupling matrix (MCM), a RERA estimating function would be constructed for estimating the FF sources' DOAs, which could reduce the multi parameter spectrum search into a 2D spectrum search. Then, with the FF sources' DOA estimates, the MCM can be reconstructed. After the mutual coupling effect elimination, another differencing covariance RERA estimator is formed to estimate the NF sources' DOAs. Finally, after estimating the DOAs of both NF and FF sources, a 3D MUSIC spectrum search in the DOA and range joint domain would be reduced to the one dimensional (1D) spectrum search only in the range domain.

2. Signal Model

Consider that K (FF and NF) narrowband and independent sources impinge on a symmetric UCA, as shown in Fig. 1. This uniform circular array is composed of $L = 2M$ ($M \in \{m | m \in \mathrm{N}^{+}, m > 1\}$) omni-directional sensors with the radius being R. The authors assume that there are K_1 NF incident sources in the Fresnel Region and the rest K_2 incident sources are FF sources, where $K_2 = K - K_1$.

Firstly, we model the ideal array received signal vector model of an ideal array, without any unknown mutual coupling effect. Without loss of generality, all the sensors

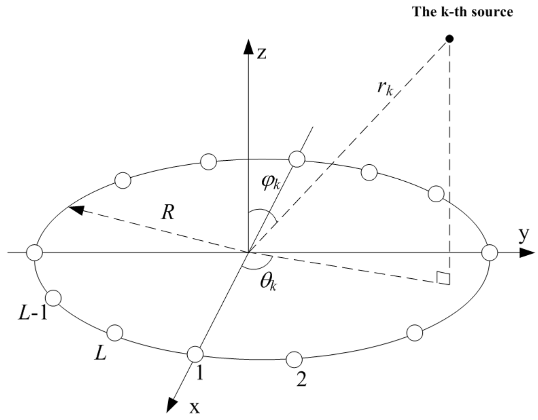

Fig. 1. The uniform circular array configuration.

are located on the xy-plane and the UCA center is set as the origin of the coordinate. At the same time, the FF source comes from (θ_k, φ_k) and the NF source comes from $(\theta_k, \varphi_k, r_k)$, where $\theta_k \in [0, 2\pi)$ is the azimuth angle measured counterclockwise from the x-axis and $\varphi_k \in [0, \pi/2]$ is the elevation angle measured downward from the z-axis. $r_k \in [0.62(D^3/\lambda)^{1/2}, 2D^2/\lambda)$ denotes the range of NF source, and $r_k \in [2D^2/\lambda, \infty)$ is the range of FF source, respectively. Therefore, $r_k \in [0.62(D^3/\lambda)^{1/2}, \infty)$ denotes the range of mixed sources measured from the UCA center, where $D = 2R$ represents the aperture of the array and λ symbolizes the incident sources wavelength. Consequently, the signal vector received by the l-th sensor can be modeled as

$$x_l(t) = \sum_{k=1}^{K_1} s_k(t) \exp\left[(\mathrm{j}2\pi / \lambda) r_{l,k} \right] + \sum_{k=1+K_1}^{K} s_k(t) \exp\left[(\mathrm{j}2\pi R / \lambda) \Theta_{l,k} \right] + n_l(t), \quad l = 0, 1, \cdots, L-1, \tag{1}$$

$$\Theta_{l,k} = \cos(\theta_k - 2\pi l / L) \sin(\varphi_k) \tag{2}$$

where $s_k(t)$ is the k-th narrowband source, $n_l(t)$ is the additive Gaussian noise, and noises in different sensors are independent with the same variance σ_n^2. Here, $r_{l,k}$ is the distance between the k-th source and the l-th sensor, which has the following form

$$r_{l,k} = \sqrt{r_k^2 + R^2 - 2 r_k R \Theta_{l,k}} - r_k. \tag{3}$$

According to the Taylor series expansion, formula (3) can be approximately given as follows

$$r_{l,k} \approx R\Theta_{l,k} - R^2 / 2r_k (1 - \Theta_{l,k}^2). \tag{4}$$

Then formula (1) can be expressed as

$$x_l(t) = \sum_{k=1}^{K_1} s_k(t) \exp\left\{ (\mathrm{j}2\pi R / \lambda) \left[\Theta_{l,k} - R / (2r_k)(1 - \Theta_{l,k}^2) \right] \right\} + \sum_{k=1+K_1}^{K} s_k(t) \exp\left[\mathrm{j}(2\pi R / \lambda) \Theta_{l,k} \right] + n_l(t). \tag{5}$$

As a result, it is obvious that the FF source can be seen as a generalized NF source, whose range parameter increases towards infinite.

According to the discussion in [5], the amplitude of mutual coupling coefficient (MCC) is in inverse proportion to the physical distance between each pair of sensors. In another word, the MCCs between neighboring sensors with a same adjacent space are almost equal to each other. Besides, the MCC would be approximately equal to zero when any two sensors are located enough far away. Unfortunately, most of the aforementioned algorithms work without unknown mutual coupling effect elimination, which would lead to fatal performance degradation of these algorithms.

As known that under the condition of the same number of sensors, the UCA can have larger aperture than that of ULA without DOA ambiguity, i.e., there would be less MCCs in a UCA than that in a ULA.

According to [5], the authors firstly model an $L \times L$ MCM of the UCA containing $P+1$ ($P < M-1$) nonzero MCCs, the symmetric Toeplitz matrix $\mathbf{C}$ can be modeled as the following

$$\mathbf{C} = \begin{bmatrix} 1 & c_1 & \cdots & c_P & 0 & \cdots & 0 & c_P & \cdots & c_1 \\ c_1 & 1 & c_1 & \ddots & c_P & 0 & \ddots & 0 & \ddots & \vdots \\ \vdots & c_1 & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & c_P \\ c_P & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & 0 \\ 0 & c_P & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & 0 & \vdots \\ \vdots & 0 & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & c_P & 0 \\ 0 & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & c_P \\ c_P & 0 & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & c_1 & \vdots \\ \vdots & \ddots & \ddots & \ddots & 0 & c_P & \ddots & c_1 & 1 & c_1 \\ c_1 & \cdots & c_P & 0 & \cdots & 0 & c_P & \cdots & c_1 & 1 \end{bmatrix}. \quad (6)$$

Therefore, the received signal vector under the unknown mutual coupling can be expressed in a matrix form

$$\mathbf{X}(t) = \mathbf{C}\mathbf{A}_{\mathrm{N}}\mathbf{S}_{\mathrm{N}}(t) + \mathbf{C}\mathbf{A}_{\mathrm{F}}\mathbf{S}_{\mathrm{F}}(t) + \mathbf{N}(t) \quad (7)$$

where $\mathbf{S}_{\mathrm{N}}(t)$ and $\mathbf{S}_{\mathrm{F}}(t)$ denote the NF and FF signal vectors,

$$\mathbf{S}_{\mathrm{N}}(t) = [s_1(t), \cdots, s_{K_1}(t)]^{\mathrm{T}}, \quad (8)$$

$$\mathbf{S}_{\mathrm{F}}(t) = [s_{1+K_1}(t), \cdots, s_K(t)]^{\mathrm{T}}. \quad (9)$$

$\mathbf{N}(t)$ signifies $L \times 1$ dimensional complex noise vector,

$$\mathbf{N}(t) = [n_1(t), \cdots, n_M(t)]^{\mathrm{T}}, \quad (10)$$

and $\mathbf{A}_{\mathrm{N}}$ and $\mathbf{A}_{\mathrm{F}}$ denote the steering vectors of NF source and FF source, respectively as

$$\mathbf{A}_{\mathrm{N}} = [\mathbf{a}(\theta_1, \varphi_1, r_1), \cdots, \mathbf{a}(\theta_{K_1}, \varphi_{K_1}, r_{K_1})], \quad (11)$$

$$\mathbf{A}_{\mathrm{F}} = [\mathbf{a}(\theta_{K_1+1}, \varphi_{K_1+1}, \infty), \cdots, \mathbf{a}(\theta_K, \varphi_K, \infty)], \quad (12)$$

$$\mathbf{a}(\theta_k, \varphi_k, r_k) = \begin{bmatrix} \mathrm{e}^{(\mathrm{j}2\pi R/\lambda)\left[\Theta_{1,k} - R/(2r_k)(1-\Theta_{1,k}^2)\right]}, \cdots, \\ \mathrm{e}^{(\mathrm{j}2\pi R/\lambda)\left[\Theta_{L,k} - R/(2r_k)(1-\Theta_{L,k}^2)\right]} \end{bmatrix}^{\mathrm{T}}, \quad (13)$$

$$\mathbf{a}(\theta_k, \varphi_k, \infty) = [\mathrm{e}^{(\mathrm{j}2\pi R/\lambda)\Theta_{1,k}}, \cdots, \mathrm{e}^{(\mathrm{j}2\pi R/\lambda)\Theta_{L,k}}]^{\mathrm{T}}. \quad (14)$$

Throughout the paper, the following hypotheses are assumed to hold:

1) The incoming source signals are statistically independent and zero-mean stationary random process;

2) The sensor noise is the additive Gaussian one, which is independent from the source signals;

3) The number of sources K, K_1 and K_2 are known as prior, and the number of sensors satisfies $K < L$ and $K_1 < M$.

3. Proposed Solution to Localization

3.1 Far-Field Sources DOA Estimation

According to (7) and the aforementioned assumptions, the received signal covariance matrix can be calculated by

$$\begin{aligned} \mathbf{R}_{\mathrm{x}} = E\{\mathbf{X}(t)\mathbf{X}^{\mathrm{H}}(t)\} = \mathbf{C}\mathbf{A}_{\mathrm{N}} \Sigma_{\mathrm{N}} \mathbf{A}_{\mathrm{N}}{}^{\mathrm{H}}\mathbf{C}^{\mathrm{H}} + \\ \mathbf{C}\mathbf{A}_{\mathrm{F}} \Sigma_{\mathrm{F}} \mathbf{A}_{\mathrm{F}}{}^{\mathrm{H}}\mathbf{C}^{\mathrm{H}} + \sigma_n{}^2\mathbf{I}_{L\times L} \end{aligned} \quad (15)$$

where $\mathbf{I}_{L \times L}$ is an $L \times L$ identity matrix, and Σ_{N} and Σ_{F} are diagonal matrices

$$\Sigma_{\mathrm{N}} = E\{\mathbf{S}_{\mathrm{N}}(t)\mathbf{S}_{\mathrm{N}}{}^{\mathrm{H}}(t)\}, \quad (16)$$

$$\Sigma_{\mathrm{F}} = E\{\mathbf{S}_{\mathrm{F}}(t)\mathbf{S}_{\mathrm{F}}{}^{\mathrm{H}}(t)\}. \quad (17)$$

By implementing eigenvalue decomposition (EVD) of $\mathbf{R}_{\mathrm{x}}$, the following equation holds

$$\mathbf{R}_{\mathrm{x}} = \mathbf{U}_{\mathrm{s}}\mathbf{\Lambda}_{\mathrm{s}}\mathbf{U}_{\mathrm{s}}{}^{\mathrm{H}} + \sigma_n{}^2\mathbf{U}_{\mathrm{n}}\mathbf{U}_{\mathrm{n}}{}^{\mathrm{H}} \quad (18)$$

where $\mathbf{\Lambda}_{\mathrm{s}}$ is the diagonal matrix which contains the K largest eigenvalues. At the same time, $\mathbf{U}_{\mathrm{n}}$ is the $L \times (L-K)$ eigenvectors matrix which spans the noise subspace of $\mathbf{R}_{\mathrm{x}}$, and $\mathbf{U}_{\mathrm{s}}$ is the $L \times K$ signal eigenvectors matrix of $\mathbf{R}_{\mathrm{x}}$ which spans the signal subspace.

As the fact that the MCM is a column full rank Toeplitz matrix, the authors can construct a MUSIC spectrum search function to estimate DOAs and ranges parameters, which is expressed as

$$p(\theta, \varphi, r) = \mathbf{a}^{\mathrm{H}}(\theta, \varphi, r)\mathbf{C}^{\mathrm{H}}\mathbf{U}_{\mathrm{n}}\mathbf{U}_{\mathrm{n}}{}^{\mathrm{H}}\mathbf{C}\mathbf{a}(\theta, \varphi, r). \quad (19)$$

From (19), it is obvious that the computational cost of this equation is unbearable with the unknown $\mathbf{C}$. Even if $\mathbf{C}$ is accurately estimated as a prior, it requires a 3D spectrum search to estimate and match the DOA and range parameters pair as well. In order to decrease the huge computational cost, the DOA estimation of FF sources must be decoupled from mixed sources estimates and MCM.

Referring to the discussion of mutual coupling problem with uniform linear array (ULA) in [5], $\mathbf{Ca}(\theta, \varphi, r)$ in UCA could be reformulated as

$$\mathbf{Ca}(\theta,\varphi,r) = \mathbf{B}(\theta,\varphi,r)\mathbf{c} \tag{20}$$

where $\mathbf{c}$ is the vector of $P + 1$ nonzero MCCs

$$\mathbf{c} = [1, c_1, \cdots, c_P]^{\mathrm{T}} = [1, \mathbf{c}_1^{\mathrm{T}}]^{\mathrm{T}}. \tag{21}$$

$\mathbf{B}(\theta, \varphi, r) = \mathbf{B}_1 + \mathbf{B}_2$ is composed of two $L \times (P + 1)$ matrices, and they are defined as

$$\{\mathbf{B}_1\}_{p,q} = [\mathbf{a}(\theta,\varphi,r)]_{\mathrm{mod}(p+q-2,L)+1}, \tag{22}$$

$$\{\mathbf{B}_2\}_{p,q} = \begin{cases} [\mathbf{a}(\theta,\varphi,r)]_{\mathrm{mod}(p-q+L,L)+1}, & \text{for } q \ge 2 \\ 0, & \text{otherwise} \end{cases} \tag{23}$$

where, $\{\bullet\}_{p,q}$ represents the element corresponding to the p-th row and q-th column of the matrix, $[\bullet]_p$ represents the element corresponding to p-th element of steering vector, and mod(p,q) denotes the modulus after dividing p by q.

It is obvious that $\mathbf{U}_{\mathrm{s}}$ and the combination of $\mathbf{CA}_{\mathrm{N}}$ and $\mathbf{CA}_{\mathrm{F}}$ can span the same signal subspace, and the signal subspace is orthogonal to the noise subspace spanned by $\mathbf{U}_{\mathrm{n}}$. Therefore, the following equations hold

$$\left|\mathbf{a}^{\mathrm{H}}(\theta_k,\varphi_k,r_k)\mathbf{C}^{\mathrm{H}}\mathbf{U}_{\mathrm{n}}\right|^2 = 0, \quad k = 1, \cdots K_1, \tag{24}$$

$$\left|\mathbf{a}^{\mathrm{H}}(\theta_k,\varphi_k,\infty)\mathbf{C}^{\mathrm{H}}\mathbf{U}_{\mathrm{n}}\right|^2 = 0, \quad k = 1 + K_1, \cdots K. \tag{25}$$

Therefore, based on (19), (20) and (25), the FF sources' DOAs can be estimated by the following spectrum search function

$$\begin{aligned} p(\theta,\varphi,\infty) &= \mathbf{a}^{\mathrm{H}}(\theta,\varphi,\infty)\mathbf{C}^{\mathrm{H}}\mathbf{U}_{\mathrm{n}}\mathbf{U}_{\mathrm{n}}^{\mathrm{H}}\mathbf{Ca}(\theta,\varphi,\infty) \\ &= \mathbf{c}^{\mathrm{H}}\mathbf{B}^{\mathrm{H}}(\theta,\varphi,\infty)\mathbf{U}_{\mathrm{n}}\mathbf{U}_{\mathrm{n}}^{\mathrm{H}}\mathbf{B}(\theta,\varphi,\infty)\mathbf{c}^{\mathrm{H}} \\ &= \mathbf{c}^{\mathrm{H}}\mathbf{W}(\theta,\varphi)\mathbf{c}^{\mathrm{H}} \end{aligned} \tag{26}$$

where $\mathbf{W}(\theta, \varphi)$ is defined as

$$\mathbf{W}(\theta,\varphi) = \mathbf{B}^{\mathrm{H}}(\theta,\varphi,\infty)\mathbf{U}_{\mathrm{n}}\mathbf{U}_{\mathrm{n}}^{\mathrm{H}}\mathbf{B}(\theta,\varphi,\infty). \tag{27}$$

Note that $\mathbf{c} \neq \mathbf{0}$ and $\mathbf{W}(\theta, \varphi)$ is a Hermite and non-negative definite matrix. Based on the principle of RERA [28], $\mathbf{c}^{\mathrm{H}}\mathbf{W}(\theta, \varphi)\mathbf{c}$ would be zero only when $\mathbf{W}(\theta, \varphi)$ is a singular matrix. In another word, the determinant of $\mathbf{W}(\theta, \varphi)$ would be equal to zero only when both parameters φ and θ are equal to those of any FF sources' DOAs φ_k and θ_k ($k = 1 + K_1,\cdots, K$). Consequently, the FF sources' DOAs could be estimated accurately by searching the K_2 highest spectrum peaks through the following function

$$p_{\mathrm{F}}(\theta,\varphi) = \frac{1}{\det[\mathbf{W}(\theta,\varphi)]} \tag{28}$$

where det[•] signifies the determinant of a matrix. From (28), it is easy seen that $p_{\mathrm{F}}(\theta, \varphi)$ is independently separated from (26). Therefore, the computational cost of estimating FF sources' DOAs through (28) is effectively reduced compared with the multi-dimensional MUSIC spectrum search function. It is because of that only a 2D spectrum search process is required.

It is noteworthy that the proposed algorithm woks in a similar way as that defined in [28], [29]. However, the algorithm in [28] only solves the problem of pure FF signals, whereas the proposed algorithm aims to deal with the problem of mixed FF and NF signals. Moreover, the algorithm in [29] solves the mixed sources problem using a ULA. However, our work explicitly addresses the mixed sources problem under mutual coupling effect, using a UCA.

3.2 MCCs Estimation and MCM Reconstruction

After estimating FF sources' DOAs, the MCCs could be computed directly by the orthogonality between $\mathbf{Ca}(\theta_k, \varphi_k, \infty)$ ($k = K_1 + 1, K_1 + 2, \cdots, K$) and $\mathbf{U}_{\mathrm{n}}$. According to (25), the following holds

$$\begin{bmatrix} \mathbf{U}_{\mathrm{n}}^{\mathrm{H}}\mathbf{Ca}(\theta_{K_1+1},\varphi_{K_1+1},\infty) \\ \vdots \\ \mathbf{U}_{\mathrm{n}}^{\mathrm{H}}\mathbf{Ca}(\theta_K,\varphi_K,\infty) \end{bmatrix} = \mathbf{0}_{K_2(L-K)\times 1} \tag{29}$$

where $\mathbf{0}_{K2(N-K)\times 1}$ denotes the $K_2(L - K) \times 1$ zero vector. According to (20) and (21), equation (29) can be expressed as

$$\begin{bmatrix} \mathbf{U}_{\mathrm{n}}^{\mathrm{H}}\mathbf{B}(\theta_{K_1+1},\varphi_{K_1+1},\infty) \\ \vdots \\ \mathbf{U}_{\mathrm{n}}^{\mathrm{H}}\mathbf{B}(\theta_K,\varphi_K,\infty) \end{bmatrix}\mathbf{c} = \mathbf{H}\begin{bmatrix} 1 \\ \mathbf{c}_1 \end{bmatrix} = \begin{bmatrix} \mathbf{H}_1 & \mathbf{H}_2 \end{bmatrix}\begin{bmatrix} 1 \\ \mathbf{c}_1 \end{bmatrix} = \mathbf{0}_{K_2(L-K)\times 1} \tag{30}$$

where $\mathbf{H}_1$ is the first column of $\mathbf{H}$, and $\mathbf{H}_2$ is constructed of the rest P columns. With replacing the DOA parameters in (30) by the FF sources' estimates, the least square solution of $\mathbf{c}_1$ can be obtained as

$$\mathbf{c}_1 = -(\mathbf{H}_2^{\mathrm{H}}\mathbf{H}_2)^{-1}\mathbf{H}_2^{\mathrm{H}}\mathbf{H}_1. \tag{31}$$

According to the symmetric Toeplitz structure modeled in [5], the MCM can be reconstructed after all MCCs being calculated. Therefore, the reconstructed MCM could be used to eliminate the mutual coupling effects in the following signal processing process.

3.3 Near-Field Sources DOA Estimation

After estimating $\mathbf{c}_1$ and reconstructing mutual coupling matrix $\mathbf{C}$, the mutual coupling effects can be eliminated effectively. We can get

$$\begin{aligned} \mathbf{R} &= \mathbf{C}^{-1}(\mathbf{R}_{\mathrm{x}} - \sigma_{\mathrm{n}}^2\mathbf{I}_{L\times L})(\mathbf{C}^{-1})^{\mathrm{H}} \\ &= \mathbf{A}_{\mathrm{N}}\,\Sigma_{\mathrm{N}}\,\mathbf{A}_{\mathrm{N}}^{\mathrm{H}} + \mathbf{A}_{\mathrm{F}}\,\Sigma_{\mathrm{F}}\,\mathbf{A}_{\mathrm{F}}^{\mathrm{H}} = \mathbf{R}_{\mathrm{N}} + \mathbf{R}_{\mathrm{F}} \end{aligned} \tag{32}$$

where σ_n^2 denotes the noise power which can be replaced by the average of the $N-K$ smallest eigenvalues of $\mathbf{R}_x$. Based on the symmetric property of UCA configuration with an even number of sensors, the following holds

$$\begin{aligned}\Theta_{l,k} &= \cos(\theta_k - 2\pi l/L)\sin(\varphi_k) \\ &= -\cos(\theta_k - 2\pi l/L + \pi)\sin(\varphi_k) \\ &= -\Theta_{\mathrm{mod}(l+M-1,L)+1,k}.\end{aligned} \tag{33}$$

Due to the fact that $\mathbf{R}_F$ is a Hermitian matrix and $\mathbf{R}_N$ only holds a Hermitian structure, we can obtain

$$\mathbf{R}_F = \mathbf{J}\mathbf{R}_F^*\mathbf{J} \tag{34}$$

where $\mathbf{J}$ is the $L \times L$ particular matrix which on basis of the characteristics of UCA can be written as

$$\mathbf{J} = \begin{bmatrix} & \mathbf{I}_{M\times M} \\ \mathbf{I}_{M\times M} & \end{bmatrix} \tag{35}$$

where $\mathbf{I}_{M\times M}$ is an $M \times M$ identity matrix. Thus, the property differences between $\mathbf{R}_F$ and $\mathbf{R}_N$ can be utilized to implement the FF sources components elimination in the covariance matrix. Then, the differencing matrix can be expressed as

$$\begin{aligned}\Delta\mathbf{R} &= \mathbf{R} - \mathbf{J}\mathbf{R}^*\mathbf{J} \\ &= \mathbf{R}_F + \mathbf{R}_N - \mathbf{J}(\mathbf{R}_F + \mathbf{R}_N)^*\mathbf{J} \\ &= \mathbf{R}_N - \mathbf{J}\mathbf{R}_N^*\mathbf{J} \\ &= \begin{bmatrix}\mathbf{A}_N & \mathbf{J}\mathbf{A}_N^*\end{bmatrix}\begin{bmatrix}\Sigma_N & \\ & -\Sigma_N\end{bmatrix}\begin{bmatrix}\mathbf{A}_N^H \\ \mathbf{A}_N^T\mathbf{J}\end{bmatrix}.\end{aligned} \tag{36}$$

In order to estimate the NF sources' DOAs efficiently, it is necessary to analyze the geometric configuration of the UCA as shown in Fig. 1. As the fact that the UCA has symmetric geometric structure with respect to array center, the steering vector $\mathbf{a}(\theta_k,\varphi_k,r_k)$ (k = 1, 2, ···, K_1) can be expressed in a decoupled form as

$$\mathbf{a}(\theta_k,\varphi_k,r_k) = \mathbf{Z}(\theta_k,\varphi_k)\mathbf{g}(\theta_k,\varphi_k,r_k) \tag{37}$$

where $\mathbf{Z}(\theta_k,\varphi_k)$ is an $L\times M$ matrix containing only the DOA parameters, and $\mathbf{g}(\theta_k,\varphi_k,r_k)$ is an $M\times 1$ column vector.

$$\mathbf{Z}(\theta_k,\varphi_k) = \begin{bmatrix} e^{j\frac{2\pi R\Theta_{1,k}}{\lambda}} & 0 & \cdots & 0 \\ 0 & e^{j\frac{2\pi R\Theta_{2,k}}{\lambda}} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \ddots & 0 & e^{j\frac{2\pi R\Theta_{M,k}}{\lambda}} \\ e^{-j\frac{2\pi R\Theta_{1,k}}{\lambda}} & 0 & \ddots & 0 \\ 0 & e^{-j\frac{2\pi R\Theta_{2,k}}{\lambda}} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & e^{-j\frac{2\pi R\Theta_{M,k}}{\lambda}} \end{bmatrix}, \tag{38}$$

$$\mathbf{g}(\theta_k,\varphi_k,r_k) = [e^{-j\pi R^2/(\lambda r_k)(1-\Theta_{1,k}^2)},\cdots,e^{-j\pi R^2/(\lambda r_k)(1-\Theta_{M,k}^2)}]^T. \tag{39}$$

Thus, $\mathbf{J}\mathbf{a}^*(\theta_k,\varphi_k,r_k)$ (k = 1, 2, ···, K_1) can be decoupled in a similar way

$$\begin{aligned}\mathbf{J}\mathbf{a}^*(\theta_k,\varphi_k,r_k) &= \mathbf{J}\mathbf{Z}^*(\theta_k,\varphi_k)\mathbf{g}^*(\theta_k,\varphi_k,r_k) \\ &= \mathbf{Z}(\theta_k,\varphi_k)\mathbf{g}^*(\theta_k,\varphi_k,r_k)\end{aligned} \tag{40}$$

and then, by implementing the EVD of $\Delta\mathbf{R}$, the following holds

$$\Delta\mathbf{R} = \mathbf{V}_s\Delta_s\mathbf{V}_s^H + \gamma_0\mathbf{V}_n\mathbf{V}_n^H \tag{41}$$

where Δ_s is a diagonal matrix which contains $2K_1$ non-zero eigenvalues, and γ_0 is the zero eigenvalue, $\mathbf{V}_s$ is the $L \times 2K_1$ eigenvectors matrix spanning the signal subspace of $\Delta\mathbf{R}$, and $\mathbf{V}_n$ is the $L \times (L-2K_1)$ eigenvectors matrix spanning the noise subspace.

As the fact that $\mathbf{V}_s$ and the combination of $\mathbf{A}_N$ and $\mathbf{J}\mathbf{A}_N^*$ can span the same signal subspace, which is orthogonal to the noise subspace spanned by $\mathbf{V}_n$. Therefore, the following holds

$$\begin{aligned}&\mathbf{a}^H(\theta_k,\varphi_k,r_k)\mathbf{V}_n\mathbf{V}_n^H\mathbf{a}(\theta_k,\varphi_k,r_k) \\ &= \mathbf{g}^H(\theta_k,\varphi_k,r_k)\mathbf{Z}^H(\theta_k,\varphi_k)\mathbf{V}_n\mathbf{V}_n^H\mathbf{Z}(\theta_k,\varphi_k)\mathbf{g}(\theta_k,\varphi_k,r_k) \\ &= \mathbf{g}^H(\theta_k,\varphi_k,r_k)\mathbf{Q}(\theta_k,\varphi_k)\mathbf{g}(\theta_k,\varphi_k,r_k) = 0,\end{aligned} \tag{42}$$

$$\begin{aligned}&(\mathbf{J}\mathbf{a}^*(\theta_k,\varphi_k,r_k))^H\mathbf{V}_n\mathbf{V}_n^H\mathbf{J}\mathbf{a}^*(\theta_k,\varphi_k,r_k) \\ &= \mathbf{g}^T(\theta_k,\varphi_k,r_k)\mathbf{Z}^H(\theta_k,\varphi_k)\mathbf{V}_n\mathbf{V}_n^H\mathbf{Z}(\theta_k,\varphi_k)\mathbf{g}^*(\theta_k,\varphi_k,r_k) \\ &= \mathbf{g}^T(\theta_k,\varphi_k,r_k)\mathbf{Q}(\theta_k,\varphi_k)\mathbf{g}^*(\theta_k,\varphi_k,r_k) = 0\end{aligned} \tag{43}$$

where $\mathbf{Q}(\theta_k,\varphi_k)$ denotes a $M \times M$ matrix defined as

$$\mathbf{Q}(\theta_k,\varphi_k) = \mathbf{Z}^H(\theta_k,\varphi_k)\mathbf{V}_n\mathbf{V}_n^H\mathbf{Z}(\theta_k,\varphi_k). \tag{44}$$

It is obvious that $\mathbf{Q}(\theta, \varphi)$ is a Hermite non-negative definite matrix, and $\mathbf{g}(\theta, \varphi, r)$ is the non-zero steering vector. According to the property of RERA type algorithms, equations (41) and (42) would hold only when $\mathbf{Q}(\theta, \varphi)$ is rank reduced, i.e., it is a singular matrix. In another words, the determinant of $\mathbf{Q}(\theta, \varphi)$ would be equal to zero only when the θ and φ parameters are equal to those of any NF sources' DOAs. Therefore, the NF sources' DOAs can be estimated by searching the K_1 highest peaks of the spatial spectrum function, which is expressed as

$$p_N(\theta,\varphi) = \frac{1}{\det[\mathbf{Q}(\theta,\varphi)]}. \tag{45}$$

In this subsection, the covariance differencing operation in UCA eliminates the FF sources' components effectively based on the structure differences of the NF and FF sources' covariance matrices. As a conclusion, the proposed algorithm successfully avoids the 3D spectrum searching and sources classification processing with the help of covariance differencing RERA.

3.4 Near-Field Sources Range Estimation

After estimating the NF sources' DOAs and replacing the unknown DOA variable pairs in the following equation by the estimated ones, the k-th NF sources' range parameter can be estimated by

$$\hat{r}_k = \min_r \mathbf{a}^{\mathrm{H}}(\hat{\theta}_k, \hat{\varphi}_k, r)\mathbf{V}_{\mathrm{n}}\mathbf{V}_{\mathrm{n}}^{\mathrm{H}}\mathbf{a}^{H}(\hat{\theta}_k, \hat{\varphi}_k, r)\cdot \tag{46}$$

From the above equation, it shows that the estimation results of both DOA and range parameters would be paired together automatically without any parameters matching processing.

3.5 The Proposed Algorithm Summary

In the above description, the authors construct ideal models of covariance matrices to introduce the flow of the proposed algorithm. However, in practice, it is almost impossible to count an ideal covariance matrix. Hence, in algorithm execution process, $\mathbf{R}_{\mathrm{x}}$ must be replaced by an estimated one which is formed by a limited T snapshots sample, which is given as

$$\hat{\mathbf{R}}_{\mathrm{x}} = \frac{1}{T}\sum_t \mathbf{X}(t)\mathbf{X}^{\mathrm{H}}(t)\cdot \tag{47}$$

Consequently, the proposed algorithm can be summarized as following.

1. Estimate the covariance matrix through (47).
2. Eigendecompose covariance matrix to generate its noise subspace.
3. Estimate the FF sources' DOAs through the RERA estimator by (28).
4. Obtain the MCCs $\mathbf{c}$ by (31), and construct the MCM by (6).
5. Compensate the MCCs by (32).
6. Construct the differencing matrix by (36).
7. Eigendecompose the difference matrix to generate its noise subspace.
8. Estimate the DOAs of NF source through the RERA estimator by (45).
9. Estimate the range parameter of NF sources through (46).

3.6 Discussion

1) *Number of required array elements*: To get the unique solution of (45), $\mathbf{Q}(\theta,\varphi)$ must be invertible at non-incident direction, that is

$$\mathrm{rank}(\mathbf{Z}(\theta,\varphi)) \le \mathrm{rank}(\mathbf{V}_{\mathrm{n}}\mathbf{V}_{\mathrm{n}}^{\mathrm{H}})\,. \tag{48}$$

Furthermore, the rank of $\mathbf{Z}(\theta, \varphi)$ and $\mathbf{V}_{\mathrm{n}}\mathbf{V}_{\mathrm{n}}^{\mathrm{H}}$ are M and $L - 2K_1$, so the parameter identifiability condition of the algorithm is $K_1 \le M/2$.

In order to estimate the MCCs, $\mathbf{H}_2$ must be a column full rank matrix, e.g., $P \le K_2(L - K)$. Consequently, at least one FF source is required to be used for MCCs estimation.

Similarly, to get the unique solution of (28), $\mathbf{W}(\theta, \varphi)$ must be invertible at non-incident direction, and $K \le L - P - 1$ must hold. As a result, we get that $1 \le K_2 \le L - P - 1 - K_1$, where $K_1 \le M/2$.

2) *Computational complexity*: In order to compare computational complexity intuitively, CD-like algorithm and TSMUSIC-like algorithm are set as comparison objects of the proposed algorithm. For all three algorithms, the major computation processes are calculating statistical matrices, eigenvalue decomposing and spectrum searching. It is defined that the search step of azimuth $\theta \in (0°, 360°]$ is θ_Δ, the search step of elevation $\varphi \in (0°, 90°]$ is φ_Δ, and the search step of $r \in [0.62(D^3/\lambda)^{1/2},\ 2D^2/\lambda]$ is r_Δ for K_1 NF sources. We assume that N is the number of snapshots.

For TSMUSIC-like algorithm the major computations are to form two $L \times L$ matrices, and to implement the EVDs of the two matrices for spatial searching twice. Thus, the computational complexity of TSMUSIC-like algorithm is

$$2L^2N + \frac{8}{3}L^3 + \frac{180^2 L^4}{\theta_\Delta \varphi_\Delta} + K_1\frac{2D^2/\lambda - 0.62(D^3/\lambda)^{1/2}}{r_\Delta}L^2\,. \tag{49}$$

For CD-like algorithm the major computations are to form an $L \times L$ covariance matrix and an $L \times L$ noise subspace matrix, and to implement once EVD of the covariance matrix. After then, three times spatial searching are required to estimate the NF sources' DOAs, the ranges of NF sources and the FF sources' DOAs. Thus, the computational complexity of this algorithm is

$$L^2(N+1) + \frac{4}{3}L^3 + 2\frac{180^2 L^4}{\theta_\Delta \varphi_\Delta} + K_1\frac{2D^2/\lambda - 0.62(D^3/\lambda)^{1/2}}{r_\Delta}L^2\,. \tag{50}$$

The proposed algorithm constructs a second order cumulant matrix. The major computations are to implement the EVDs of the $L \times L$ covariance matrix and differencing matrix, and to perform three times spatial search for estimating DOA and range. Thus, the computational complexity of the proposed algorithm is

$$L^2N + \frac{8}{3}L^3 + 2\frac{180^2 L^4}{\theta_\Delta \varphi_\Delta} + K_1\frac{2D^2/\lambda - 0.62(D^3/\lambda)^{1/2}}{r_\Delta}L^2\,. \tag{51}$$

3) *Capacity for localizing mixed sources*: From the above analysis, it is obvious that if the FF sources and the NF sources have the same DOA, the TSMUSIC-like algorithm would be invalid. However, CD-like algorithm and the proposed algorithm can eliminate FF component when estimating the NF sources. But, CD-like algorithm ignores the mutual coupling effect.

4. Simulation Results

Some simulations are conducted in this section to evaluate the proposed algorithm. A UCA of 10 elements with radius $R = 2\lambda$ is taken into consideration.

The input signal to noise ratio (SNR) of the k-th source is defined as $10\log_{10}(\sigma_k^2 / \sigma_n^2)$, where σ_k^2 denotes the power of the k-th source, and σ_n^2 denotes the noise power. Assuming that all sources are with equal power, in the following experiments, the performance is measured by the root mean square errors (RMSE) of 200 independent Monte Carlo experiments.

It is noticed that the estimation performance of the range parameters are only for near-field sources experiment, and we would not give the estimation performance of the range parameters of FF sources.

4.1 Spectrums of DOA and Range Estimation in Presence of Mutual Coupling Effect

In the first simulation, the authors consider a scenario in where two NF sources and two FF sources coexist, and they are located at $\{\theta_1 = 50°, \varphi_1 = 45°, r_1 = 1.7\lambda\}$, $\{\theta_2 = 140°, \varphi_2 = 45°, r_2 = 2.6\lambda\}$, $\{\theta_3 = 140°, \varphi_3 = 45°, r_3 = \infty\}$ and $\{\theta_4 = 220°, \varphi_4 = 45°, r_4 = \infty\}$. In order to show the spatial spectra in an intuitive way, we set all sources with the same elevation. The number of snapshots is set as 200 and the SNR of incoming sources is set as 10 dB. And, the nonzero MCCs are set as $[1, -0.0992 + 0.0129j, 0.0018 - 0.0098j]$.

The DOA and range spectrums of the three algorithms are shown in Fig. 2 to Fig. 5. From Fig. 2, it shows that TSMUSIC-like generates four highest sharp spectrum peaks on the directions of NF and FF sources.

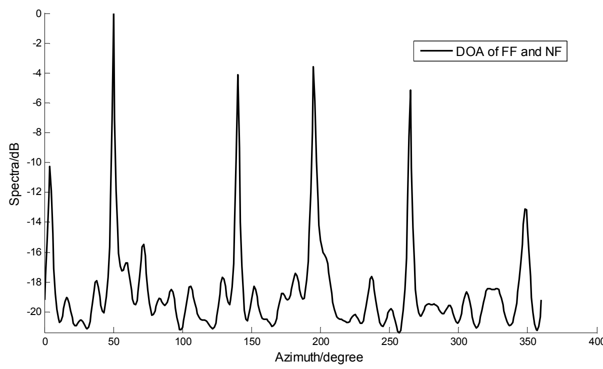

Fig. 2. Azimuth spectrum of TSMUSIC-like at $\varphi = 45°$.

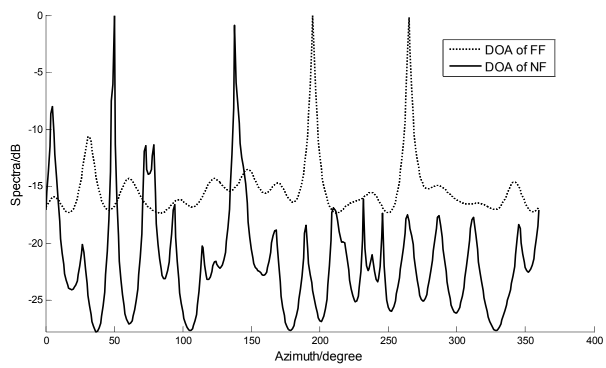

Fig. 3. Azimuth spectrum of CD-like at $\varphi = 45°$.

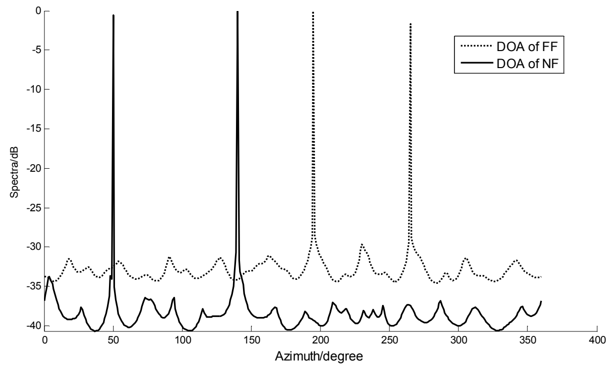

Fig. 4. Azimuth spectrum of proposed algorithm at $\varphi = 45°$.

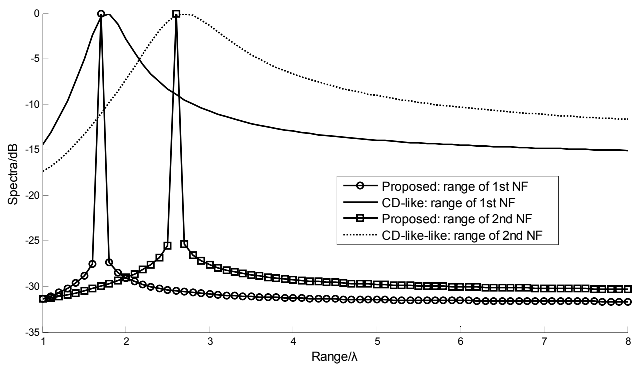

Fig. 5. Range spectrum of CD-like and the proposed algorithms.

However, there are other false peaks caused by the unknown mutual coupling effect, which would lead to false estimation. In Fig. 3, it shows that CD-like generates worse spectra of NF sources than that in Fig. 2. This is because that CD-like cannot eliminate the FF components under unknown mutual coupling. In Fig. 4, it shows that the proposed algorithm generates two sharp peaks in spectrum of NF sources and another two sharp peaks in that of FF sources, corresponding to the actual DOAs of mixed sources. It obviously shows that the DOA estimates of CD-like and TSMUSIC-like are biased caused by mutual coupling effect. It must be noted that TSMUSIC-like fails to classify NF sources between the mixed sources. Therefore, its range estimation would be invalid. As a result, the mutual coupling effect and the propagated error of DOA estimation lead reliable range parameters estimation as shown in Fig. 6, however, the proposed algorithm can perform the more accurate range estimates of the two NF sources than those estimated by CD-like.

4.2 Performance versus Snapshot Number in Presence of Mutual Coupling Effect

In the second simulation, the authors consider a scenario in which one NF source and one FF sources coexist, and the location parameters are $\{\theta_5 = 98°, \varphi_5 = 37°, r_5 = 2.2\lambda\}$ and $\{\theta_6 = 277°, \varphi_6 = 55°, r_6 = \infty\}$, with the SNR being set as 10 dB. The nonzero MCCs are set as the same as those in the first experiment and the number of snapshots varies from 100 to 1000.

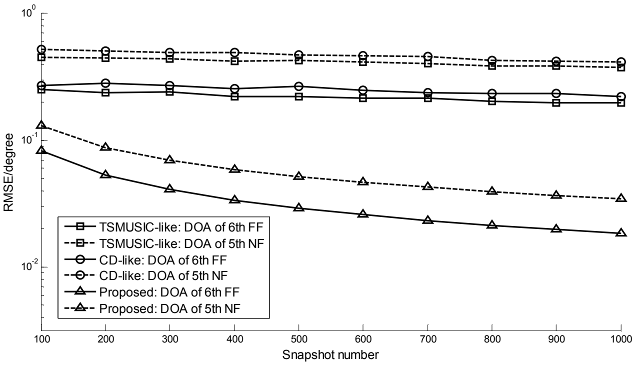

Fig. 6. RMSEs of the DOA estimates versus snapshot number.

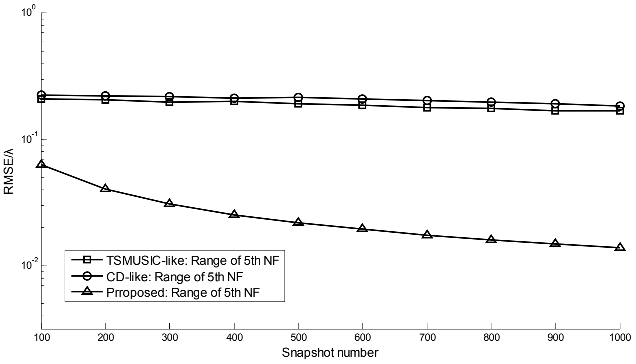

Fig. 7. RMSEs of the range estimates versus snapshot number.

The RMSEs of the DOA and range estimates, as the snapshot number changes, are shown in Fig. 6 and Fig. 7. It obviously shows that both the DOA and the range estimation RMSEs of the proposed algorithm decrease monotonically as the snapshot number increases. It is due to the fact that a larger sampling number will produce better estimate of the covariance matrix for stationary data. Compared with the proposed algorithm, both the DOA and range RMSEs of the other two algorithms no longer decrease as the number of snapshots increases. It is because of steering mismatching caused by mutual coupling effect.

4.3 Performance versus SNR in Presence of Mutual Coupling Effect

In the third simulation, the almost all simulation conditions are adopted as same as those in the second experiment except that the number of snapshots is set as 200, and the SNR varies from −5 dB to 20 dB.

The RMSEs of the DOA and range estimates, as the changes of SNR, are shown in Fig. 8 to Fig. 9. In Fig. 8, it shows that only the proposed algorithm can provide satisfactory DOA estimation performance of mixed sources. As a result, the proposed algorithm outperforms the other two algorithms in both DOA and range estimation in Fig. 9. Moreover, the increasing SNR is no longer helpful for TSMUSIC-like and CD-like due to the model error of covariance matrices caused by dominating mutual coupling error.

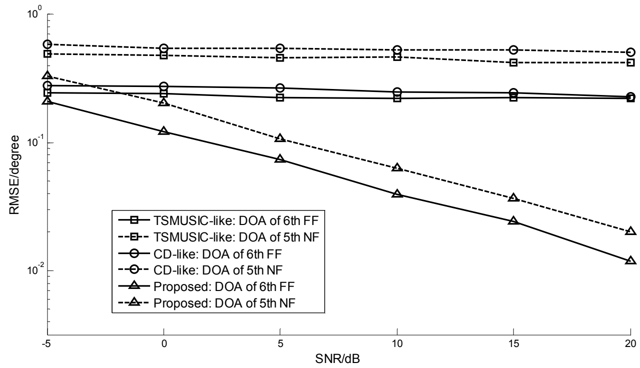

Fig. 8. RMSEs of the DOA estimates versus SNR.

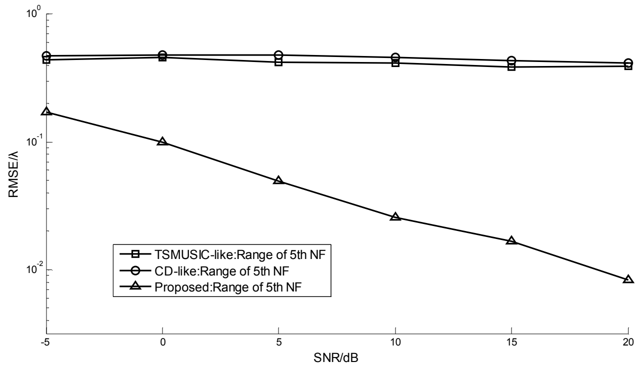

Fig. 9. RMSEs of the range estimates versus SNR.

5. Conclusions

In this paper, a high performance and low complexity localization algorithm for mixed NF and FF sources classification and localization in the presence of unknown mutual coupling in UCA is proposed. Compared with aforementioned algorithms, the proposed algorithm is effective in mixed sources classification and localization, and it can provide better DOA and range estimation performance under the mutual coupling effect. In addition, for computational complexity, the proposed algorithm successfully avoids multi-dimensional spectrum search (with respect to MCCs and range), parameter matching and high order cumulant. Finally, many simulation results give forceful proof of that the proposed algorithm is efficient for the problem of mixed sources classification and localization under unknown mutual coupling in UCA.

Moreover, in many references, the mutual coupling effect is usually modelled as a symmetric Toeplitz matrix simply with a limited number of nonzero MCCs. In other words, the number of nonzero MCCs is known as prior knowledge in abovementioned papers. However, in practice, it is much more complicated due to the complex microwave propagation environment, and we must estimate the accurate number of nonzero MCCs firstly, which would affect the estimation performance. Therefore, estimating the accurate number of nonzero MCCs and constructing the more accurate MCM are still worthy to do future research.

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