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Passive localization of mixed sources jointly using MUSIC and sparse signal reconstruction

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ABSTRACT

Source localization for mixed far-field and near-field sources is considered. By constructing the second-order statistics domain data of array which is only related to DOA parameters of mixed sources, we obtain the DOA estimation of all sources using the weighted ℓ_1-norm minimization. And then, we use MUSIC spectral function to distinguish the mixed sources as well as to provide a more accurate DOA estimation of far-field sources. Finally, a mixed overcomplete matrix on the basis of DOA estimation is introduced in the sparse signal representation framework to estimate range parameters. The performance of the proposed method is verified by numerical simulations and is also compared with two existing methods.

1. Introduction

Source localization is a problem of great importance in many fields such as radar, sonar, electronic surveillance and seismic exploration [1]. Various high-resolution methods like MUSIC [2] and ESPRIT [3] have been proposed to obtain the direction-of-arrival estimation of far-field sources in the past decades. When the sources are located at the near-field region, several efficient methods such as the two-dimensional (2-D) MUSIC [4], the high-order ESPRIT [5] and the path following method [6] are also available.

In some practical applications, such as speaker localization using microphone arrays [7] and guidance (homing) systems [8], both far-field and near-field sources may be encountered. In this case, all the methods above may not be expected to give satisfactory results since they will mismatch the signal model. By constructing two special cumulant matrices, Liang et al. [9] have developed a two-stage MUSIC method for locating mixed sources. Instead of using cumulant, He et al. [10] present a new approach by efficiently using the second-order statistics based MUSIC method. Recently, Wang et al. [11] utilize sparse signal reconstruction rather than the subspace technique for mixed source localization, which exploits the property that the locations of the point source signals are usually very sparse relative to the entire spatial domain. It achieves high resolution and high estimation accuracy. However, there exists a problem in this method [11] that the range grids set should include both near-field region and far-field region, whether the source is near-field one or far-field one. This will bring considerable computational burden. In addition, this method would fail in the presence of Gaussian sources since it uses fourth-order cumulant [10].

In this paper, we propose a new mixed source localization method jointly using MUSIC and sparse signal representation. The proposed method includes three steps: (i) transform the output data of array into second-order statistics data and obtain the DOA estimation of all sources using the weighted ℓ_1-norm minimization; (ii) utilize MUSIC spectra function to distinguish the mixed sources and successively obtain a more accurate azimuth DOA estimation of far-field sources; (iii) construct mixed overcomplete matrix and apply it to estimate range parameters of near-field sources. The proposed method is better suited for both Gaussian and Non-Gaussian sources. Compared with the method addressed in [10], the proposed method can provide an improved azimuth DOA and range estimation accuracy of the near-field sources. Moreover, it also performs better in estimating azimuth DOA of far-field sources, as well as range parameters of near-field sources in comparison with the method addressed in [11]. In addition, the computational complexity of the proposed method is much lower than that of [11].

The reminder of this paper is organized as follows: The mixed near-field and far-field signal model based on a symmetric uniform linear array is introduced in Section 2. The mixed source localization method jointly using MUSIC and sparse signal reconstruction is proposed in Section 3. Simulation results are presented in Section 4. Conclusions are drawn in Section 5.

2. Mixed near-field and far-field signal model

We consider the data model introduced by Liang and Liu [9] for an array of $2M+1$ sensors receiving K (near-field or far-field)

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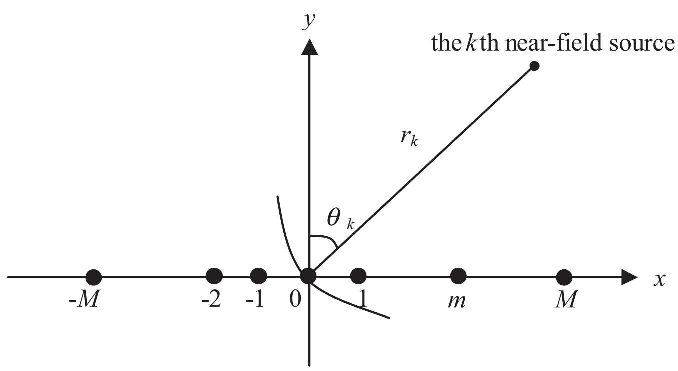

Fig. 1. Uniform linear array configuration.

source signals. The array configuration is shown in Fig. 1. Let the array center be the phase reference point. After sampled with a proper rate that satisfies the Nyquist rate, the signal received by the mth sensor can be expressed as

$$y_m(t) = \sum_{k=1}^{K} s_k(t)e^{j\tau_{mk}} + n_m(t), \qquad t = 0, \ldots, N-1 \tag{1}$$

where N is the snapshot number, $s_k(t)$ denotes the kth source signal, $n_m(t)$ represents the additive Gaussian noise, and τ_{mk} indicates the delay associated with the kth source signal propagation time from 0th to mth sensor. If the kth source is near-field one, τ_{mk} can be given by

$$\tau_{mk} = m\gamma_k + m^2\phi_k \tag{2}$$

where γ_k and ϕ_k are called electric angles and given by

$$\gamma_k = -2\pi \frac{d}{\lambda} \sin(\theta_k) \tag{3}$$

$$\phi_k = \pi \frac{d^2}{\lambda r_k} \cos^2(\theta_k) \tag{4}$$

where θ_k and r_k are the azimuth DOA and range of the kth near-field sources, respectively. λ and d denote the carrier wavelength and intersensor spacing, respectively. Otherwise, if the kth source is far-field one, τ_{mk} has the following form:

$$\tau_{mk} = m\gamma_k. \tag{5}$$

Thus, the far-field source can be regarded as a special case of near-field source with $\phi_k = 0$ or $r_k = \infty$.

Consequently, the mixed near-field and far-field signal model can be rewritten as

$$\mathbf{y}(t) = \mathbf{A}\mathbf{s}(t) + \mathbf{n}(t) = \mathbf{A}_N\mathbf{s}_N(t) + \mathbf{A}_F\mathbf{s}_F(t) + \mathbf{n}(t) \tag{6}$$

where $\mathbf{A} = [\mathbf{A}_N \ \mathbf{A}_F]$, $\mathbf{s} = \left[\mathbf{s}_N^T \quad \mathbf{s}_F^T\right]^T$, and

$$\mathbf{A}_N = [\mathbf{a}_N(\gamma_1, \phi_1), \ldots, \mathbf{a}_N(\gamma_{K_1}, \phi_{K_1})] \tag{7}$$

$$\mathbf{A}_F = [\mathbf{a}_F(\gamma_{K_1+1}), \ldots, \mathbf{a}_F(\gamma_K)] \tag{8}$$

$$\mathbf{a}_N(\gamma_k, \phi_k) = \left[e^{-jM\gamma_k + M^2\phi_k}, \ldots, 1, \ldots, e^{jM\gamma_k + M^2\phi_k}\right]^T \tag{9}$$

$$\mathbf{a}_F(\gamma_k) = [e^{-jM\gamma_k}, \ldots, 1, \ldots, e^{jM\gamma_k}]^T \tag{10}$$

$$\mathbf{s}_N(t) = \left[s_1(t), \ldots, s_{K_1}(t)\right]^T \tag{11}$$

$$\mathbf{s}_F(t) = \left[s_{K_1+1}(t), \ldots, s_K(t)\right]^T \tag{12}$$

where K_1 and $K - K_1$ denote the number of near-field sources and far-field sources respectively and the superscript T stands for the transpose operator.

Throughout the rest of the paper, the following assumptions are required:

1. The source signals are statistically independent, zero mean stationary processes.
2. The sensor noise is zero-mean, circular Gaussian, spatially uniformly white and independent from the source signals.
3. The sensor array is a symmetric uniform linear array composed of $2M+1$ sensors. To avoid an ambiguity of phase in mixed sources localization scenario, the inter-element spacing is $d \le \lambda/4$, and the source number is $K < M+1$.

3. Proposed method

3.1. DOA estimation of all sources

In this paper, second-order statistics is considered. The array covariance matrix is defined as

$$\mathbf{R} = \mathrm{E}\left\{\mathbf{y}(t)\mathbf{y}^H(t)\right\} = \mathrm{A}\mathrm{P}\mathbf{A}^H + \sigma^2\mathbf{I} \tag{13}$$

where $\mathbf{P} = \mathrm{E}\left\{\mathbf{s}(t)\mathbf{s}^H(t)\right\} = \mathrm{diag}\{P_1, \ldots, P_K\}$ is the signal covariance matrix, P_k is the power of kth signal, σ^2 is the noise variance, $\mathrm{E}\{\cdot\}$ and H denote the expectation and the conjugate transpose operation, respectively. The symbol $\mathrm{diag}\{z_1, z_2\}$ represents a diagonal matrix with diagonal entries z_1 and z_2.

Let $r_{p,q}$ be the cross-correlation coefficient of the pth and qth array output, which is defined by

$$r_{p,q} = \mathrm{E}\left\{y_p(t)y_q^*(t)\right\} \quad = \sum_{k=1}^{K} a_p(\gamma_k, \phi_k)a_q^*(\gamma_k, \phi_k)P_k + \sigma^2\delta_{p,q} \tag{14}$$

where $a_p(\gamma_k, \phi_k)$ is the (p, k)th element of $\mathbf{A}$. $\delta_{p,q}$ denotes the Dirac delta function. From (13), we can obtain that the anti-diagonal elements of array covariance matrix $\mathbf{R}$ can be expressed as

$$\mathbf{R}(i, 2M+2-i) = \sum_{k=1}^{K} P_k e^{-j2(M+1-i)\gamma_k} + \sigma^2\delta_{i,2M+2-i} \tag{15}$$

where $i \in [1, 2M+1]$. Therefore, for all i, we can form the following $(2M+1) \times 1$ signal model

$$\boldsymbol{\Gamma} = [\mathbf{R}(1, 2M+1), \ldots, \mathbf{R}(2M+1, 1)]^T = \mathbf{BP} + \sigma^2\mathbf{I}_M \tag{16}$$

where

$$\mathbf{B} = [\mathbf{b}(\theta_1), \ldots, \mathbf{b}(\theta_K)] \tag{17}$$

$$\mathbf{b}(\theta_k) = [e^{-j2M\gamma_k}, e^{-j2(M-1)\gamma_k}, \ldots, 1, \ldots, e^{j2M\gamma_k}]^T \tag{18}$$

$\mathbf{P} = [P_1, \ldots, P_K]^T$ and $\mathbf{I}_M$ is a $(2M+1) \times 1$ vector, whose Mth element is one and the others are zeros. Assume that the number of sources K is known or correctly estimated by the Akaike information criterion (AIC) or the minimum description length (MDL) detection criterion [12]. Then the noise variance can be obtained by the average of the $2M+1-K$ smallest eigenvalues of $\mathbf{R}$. Consequently, we can obtain a noise-free model

$$\boldsymbol{\Gamma}_1 = \boldsymbol{\Gamma} - \sigma^2\mathbf{I}_M = \mathbf{BP}. \tag{19}$$

Note that formulation (19) can be considered as a spatial signature of the sources, which is dependent only on the information of DOAs.

In sparse signal representation framework, Eq. (19) can be rewritten as

$$\boldsymbol{\Gamma}_1 = \mathbf{B}_\gamma(\Theta)\mathbf{P}_{\overline{K}} \tag{20}$$