Signal Processing 143 (2018) 134–139

Contents lists available at ScienceDirect

Signal Processing

journal homepage: www.elsevier.com/locate/sigpro

Short communication

# Classification and localization of mixed near-field and far-field sources using mixed-order statistics☆

Zhi Zheng*, Jie Sun, Wen-Qin Wang, Haifen Yang

*School of Communication and Information Engineering, University of Electronic Science and Technology of China, Chengdu 611731, China*

ARTICLE INFO

*Article history:*
Received 23 July 2017
Revised 27 August 2017
Accepted 31 August 2017
Available online 1 September 2017

*Keywords:*
Mixed sources
Source localization
Near-field
Far-field
Fourth-order cumulant

ABSTRACT

In this paper, a novel algorithm based on mixed-order statistics is proposed for mixed near-field and far-field source localization. Firstly, the direction-of-arrivals (DOAs) of far-field signals are estimated using the conventional MUSIC method based on second-order statistics. Then, a special fourth-order cumulant matrix of the array output is constructed, which is only related to DOA parameters of mixed sources. After estimating the kurtosis of far-field signals, the related far-field components can be removed from the constructed cumulant matrix and the near-field components can be derived. With the near-field data in the cumulant domain, the DOA estimations of near-field sources can be performed using high-order MUSIC spectrum. Finally, with the near-field DOA estimates, the range parameters of near-field sources can be obtained via one-dimensional search. The proposed algorithm involves neither two-dimensional search nor additional parameter pairing processing. Moreover, it can achieve a more reasonable classification of the source types. Simulations results demonstrate the advantages of the proposed algorithm in comparison to the existing methods.



## 1. Introduction

Source localization is an important topic in many array processing applications such as radar, sonar, wireless communications, electronic surveillance and seismic exploration [1–4]. In the past few decades, it has received considerable attention, and various high-resolution algorithms like MUSIC [5] and ESPRIT [6] have been developed to perform the direction-of-arrival (DOA) estimation of far-field (FF) sources under the plane waves hypothesis. In the near-field (NF) sources scenario, both DOA and range parameters should be estimated since the plane waves assumption is not valid, and some near-field localization algorithms [7–20] are also available. However, in some practical applications, both near-field and far-field sources may coexist, such as speaker localization using microphone arrays. In the mixed sources scenario, the aforementioned algorithms may fail to localize the mixed sources.

To cope with this issue, some algorithms have been recently presented. Based on two special comulant matrices of array outputs, Liang et al. [21] presented a two-stage MUSIC (TSMUSIC) algorithm to deal with the problem of mixed near-field and far-field source localization. However, the TSMUSIC algorithm is based on high-order statistics (HOS) and thus it is computationally inefficient and can not deal with Gaussian sources. Motivated by the above drawback, He et al. [22] developed the MBODS method based on second-order statistics (SOS). The MBODS method can correctly distinguish the types of sources and avoid both two-dimensional (2-D) search and high-order statistics calculations. However, when locating the near-field sources, the MBODS method suffers from partial aperture loss, reducing the accuracy to some extent. Later, Liu et al. [23] presented another SOS-based method for mixed far-field and near-field source localization. Compared with the MBODS method, the method of Liu and Sun [23] can achieve a more reasonable classification of the signal types, reduce the aperture loss, as well as enhance the localization accuracy of near-field sources. Resorting to a special sparse array geometry, Wang et al. [24] presented a mixed-order MUSIC algorithm, which has improved the accuracy and resolution of mixed source localization. Using the ESPRIT-Like and polynomial rooting methods, Jiang et al. [25] presented a new algorithm for mixed source localization. The method of Jiang et al. [25] not only offers better performance for both the DOA and range estimations, but also requires less computational cost than the algorithms of Liang and co-workers [21,22]. Wang et al. [26] adopted the sparse reconstruction technique to locate mixed sources, which has some salient advantages in resolution and accuracy over the subspace-based techniques. However, the sparse reconstruction method [26] will meet with some performance deterioration under unknown the number

☆ Fully documented templates are available in the elsarticle package on CTAN.

* Corresponding author.
*E-mail addresses:* zz@uestc.edu.cn (Z. Zheng), sunj@std.uestc.edu.cn (J. Sun), wqwang@uestc.edu.cn (W.-Q. Wang), yanghf@uestc.edu.cn (H. Yang).

http://dx.doi.org/10.1016/j.sigpro.2017.08.025
0165-1684/

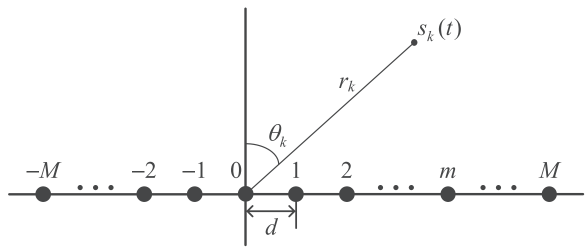


**Fig. 1.** Uniform linear array configuration.

of sources. To overcome the shortcoming, Tian et al. [27] proposed a mixed source localization algorithm using the sparse representation of two special cumulant vectors. Liu et al. [28] propose an ESPRIT method for localization of mixed far-field and near-field cyclostationary sources. The ESPRIT algorithm can greatly reduce the computational cost and achieve automatic pairing of the DOA and range estimates. Wang et al. [29] proposed another low-complexity algorithm using array partition and high-order cumulants, which can alleviate the array aperture loss and avoid spectral search. By taking advantage of the differences between the far-field and the near-field covariance matrices, the spatial differencing algorithms of Liu and Sun [30,31] are presented for mixed source classification and localization. Compared with the previous techniques, the spatial differencing methods can not only achieve a more reasonable classification of the source types, but also provide higher estimation accuracy.

In this paper, we propose a novel algorithm for mixed source localization based on second-order and fourth-order statistics. The proposed algorithm is implemented by three stages: (i) The DOAs of far-field sources are estimated by the conventional MUSIC method. (ii) A fourth-order cumulant matrix containing only DOA information of sources is constructed. After estimating the kurtosis of far-field signals, the related far-field components can be removed from the constructed cumulant matrix and the near-field components are obtained. With the near-field components in cumulant domain, the DOAs of near-field sources can be obtained using high-order MUSIC spectrum. (iii) With the near-field DOA estimates, the range parameters of near-field sources are obtained by one-dimensional (1-D) search. Our approach requires neither 2-D search nor extra parameter pairing processing, and it can realize a more reasonable classification of the signals types. Its superiorities over the traditional methods are verified by simulation results.

The rest of this paper is organized as follows. The received signal model of mixed sources along with some basic assumptions are described in Section 2. A novel approach for mixed source classification and localization is proposed in Section 3. Simulations and results are provided in Section 4. Finally, conclusions are drawn in Section 5.

## 2. Signal model and basic assumptions

Consider $K$ (near-field or far-field) narrowband sources impinging on a symmetric uniform linear array with $2M+1$ elements and inter-element spacing $d$, as depicted in Fig. 1. Let the array center be the phase reference point, the signal received by the $m$th sensor can be expressed as

$$y_m(t) = \sum_{k=1}^{K} s_k(t) e^{j\tau_{mk}} + n_m(t) \tag{1}$$

where $s_k(t)$ is the $k$th signal waveform, $n_m(t)$ denotes the $m$th sensor noise, and $\tau_{mk}$ represents the propagation time of the $k$th source between the 0th and $m$th sensor. When the $k$th source is a near-field one, $\tau_{mk}$ is given by

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

where $\omega_k$, $\phi_k$ have the following forms:

$$\omega_k = -2\pi \frac{d}{\lambda} \sin\theta_k, \tag{3}$$

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

where $\lambda$ is the wavelength of the incoming signal. $\theta_k$ and $r_k$ denote the DOA and range of the $k$th source at the phase origin, respectively. Otherwise, when the $k$th source is located in the far-field region, the range parameter is $r_k \to \infty$, and the associated parameter $\phi_k$ is approximately equal to zero. Then $\tau_{mk}$ can be expressed as

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

In matrix form, (1) can be written as

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

where $\mathbf{y}(t)$ and $\mathbf{n}(t)$ are $(2M+1) \times 1$ complex vectors, and

$$\mathbf{y}(t) = [y_{-M}(t), \ldots, y_0(t), \ldots, y_M(t)]^T \tag{7}$$

$$\mathbf{A}_N = [\mathbf{a}(\theta_1, r_1), \ldots, \mathbf{a}(\theta_{K_1}, r_{K_1})] \tag{8}$$

$$\mathbf{A}_F = [\mathbf{a}(\theta_{K_1+1}), \ldots, \mathbf{a}(\theta_K)] \tag{9}$$

$$\mathbf{s}_N(t) = [s_1(t), \ldots, s_{K_1}(t)]^T \tag{10}$$

$$\mathbf{s}_F(t) = [s_{K_1+1}(t), \ldots, s_K(t)]^T \tag{11}$$

$$\mathbf{n}(t) = [n_{-M}(t), \ldots, n_0(t), \ldots, n_M(t)]^T \tag{12}$$

where

$$\mathbf{a}(\theta_k, r_k) = \left[ e^{j(-M\omega_k + M^2\phi_k)}, \ \ldots, 1, \ldots, \right. \\ \left. e^{j(M\omega_k + M^2\phi_k)} \right]^T \tag{13}$$

denotes the $(2M+1) \times 1$ steering vector, and the superscript $T$ denotes the transpose. It is worth mentioning that in signal model (6), the first $K_1$ sources are assumed to be near-field sources and the remaining $(K - K_1)$ are far-field sources.

Throughout this paper, the following assumptions are required to hold:

1. The source signals are statistically independent, zero-mean random processes with nonzero kurtosis, and all signals impinge on the receiver array from distinct directions.
2. The sensor noise is the additive spatially white Gaussian one with zero-mean, and independent of the source signals.
3. The sensor array is a ULA with inter-element spacing $d = \lambda/4$, and the source number is less than the number of elements, namely, $K < 2M+1$.

## 3. Proposed algorithm

### 3.1. DOA estimations of far-field sources

According to (6), we can obtain the covariance matrix of the array received data $\mathbf{y}(t)$ as

$$\mathbf{R} = E\{\mathbf{y}(t)\mathbf{y}^H(t)\} \tag{14}$$