Digital Signal Processing 83 (2018) 261–270

Contents lists available at ScienceDirect

Digital Signal Processing

www.elsevier.com/locate/dsp

An efficient method for angular parameter estimation of incoherently distributed sources via beamspace shift invariance

Zhi Zheng [a,*], Jian Lu [a], Wen-Qin Wang [a], Haifen Yang [a], Shunsheng Zhang [b]

[a] School of Information and Communication Engineering, University of Electronic Science and Technology of China, Chengdu 611731, China
[b] Research Institute Electronic Science and Technology, University of Electronic Science and Technology of China, Chengdu 611731, China

ARTICLE INFO

Article history:
Available online 20 September 2018

Keywords:
Direction-of-arrival (DOA)
Angular spread
Incoherently distributed (ID) sources
Uniform linear array (ULA)
Beamspace shift invariance

ABSTRACT

In this paper, we propose a beamspace-based method for nominal direction-of-arrival (DOA) and angular spread estimation of incoherently distributed (ID) sources using a uniform linear array (ULA). Firstly, with generalized array manifold of the ULA, we obtain the beamspace array manifold by performing beamspace transformation on the received vector of two overlapping subarrays, and further derive the beamspace shift invariance structure via designing appropriate beamforming matrix. Next, the total least squares approach is used to estimate the nominal DOAs of ID sources. Finally, with the DOA estimates, the corresponding angular spreads are obtained by means of the central moments of the angular distribution. The proposed method does not involve any spectral search and reduces the dimension of matrix operations, thus it is obviously more efficient than the traditional algorithms. Simulation results indicate that our proposed algorithm is comparable to the existing algorithms when the number of sensors is large.

1. Introduction

Source localization, which is referred to as the estimation of direction-of-arrival (DOA), is an important topic in array signal processing and has attracted considerable attention in the past decades [1]. Therefore, various high-resolution methods like MUSIC [2] and ESPRIT [3] were developed to perform DOA estimation. Most of them are based on point source model, that is, the energy of each source is assumed to be concentrated at discrete direction. But in applications such as radar, sonar, mobile communications, the angular spread effect cannot be neglected due to multipath propagation [4]. Therefore, a “scattered” or “distributed” source model is more appropriate [5,6], where the received signal is characterized by two angular parameters, i.e., the nominal DOA and the angular spread. Depending on the correlation among different rays, the distributed sources can be categorized into coherently distributed (CD) and incoherently distributed (ID) sources [7]. A source is called CD sources if the signal components arriving from different directions are delayed and scaled replicas of the same signal, whereas in the ID case, all signals coming from different directions are assumed to be uncorrelated.

In the past decades, the parameter estimation of CD sources has been well studied via extending the classical methods for point sources [7–18]. However in case of ID sources, the parameter estimation problem becomes rather complicated since the dimension of the signal or noise subspace cannot be determined. Thus, most classical methods based on point source assumption are not easily generalized to this situation. To cope with ID sources, various special approaches have also been developed on the basis of maximum likelihood (ML), pseudo-signal subspace, generalized Capon (GC) and others.

Among the existing estimators for ID sources, the ML estimator [19] can provide optimal performance, where the likelihood function is jointly maximized for all parameters of the Gaussian model. The ML estimator has heavy computational burden because it involves a multidimensional search over a nonlinear likelihood function. While the approximate ML estimators of [20,21] exhibits suboptimal performance with lower computational load. By using a simplified signal model, another approximate ML estimator was proposed in [22]. It reduces the search dimension but is limited to a single-source scenario. These approximate ML estimators are still computationally intensive.

Subspace-based approaches are another type of popular techniques. The modifications of the classical MUSIC algorithm have given rise to the distributed source parameter estimator (DSPE) [7] and dispersed signal parameter estimator (DISPARE) [23]. But both of them can not provide consistent estimates. To overcome this

* Corresponding author.
E-mail addresses: zz@uestc.edu.cn (Z. Zheng), 201621010410@std.uestc.edu.cn (J. Lu), wqwang@uestc.edu.cn (W.-Q. Wang), yanghf@uestc.edu.cn (H. Yang), zhangss_bit@163.com (S. Zhang).

https://doi.org/10.1016/j.dsp.2018.09.003
1051-2004/

drawback, a class of weighted subspace fitting algorithms in the case of full-rank data model has been developed to provide consistent parameter estimates [24,25]. Moreover, an efficient subspace-based (ESB) estimator without eigen-decomposition was proposed in [26]. The main difficulty of these subspace-based approaches is the choice of the effective dimension of the pseudo-signal subspace, since the optimal choice depends on the unknown parameters. To tackle this issue, the GC estimator [27] was presented by generalizing the Capon method [28]. However, it assumes that the multiple sources must have identical and known angular distribution. To overcome the shortcomings of [27], a robust GC algorithm was proposed in [29]. Similar to the ML estimator, these algorithms have high computational complexity due to multidimensional search.

To reduce the computational cost, some ID sources estimators based on covariance matching [30], two-ray model and ESPRIT [3] have been proposed. For instance, the COMET-EXIP method [31] replaces the multidimensional search via two successive one-dimensional (1-D) searches. However, this algorithm suffers from ambiguity problem that limits its application in practice. This ambiguity problem was later successfully solved in [32]. Moreover, [31] and [32] can only handle a single source. In [33], a search-free covariance fitting approach is presented, where the nominal DOAs and angular spreads can be obtained from the central and noncentral moments of the angular power densities. This approach can be used for widely separated multisource scenarios with different angular distributions. However, this method requires the preliminary estimates of nominal DOAs. In [34], the authors suggested a low-complexity estimator using a two-ray approximate model for distributed sources, where each source is considered as a rank two component to the array covariance matrix. The main disadvantage of this method is that it is restricted to the single source case. In [9], an ESPRIT-based method was proposed, which derives the generalized array manifold (GAM) to obtain the closed-form solutions of nominal DOAs and angular spreads. By employing the generalized ESPRIT [35], the authors of [36] have devised the generalized ESPRIT method for ID sources. Compared with the ESPRIT-based method [9], [36] can achieve better performance and deal with more sources. [9] and [36] are restricted to the array geometry with two identical and closely-deployed uniform linear arrays (ULAs) to obtain an approximate shift invariance structure, implying their limited applicability.

Beamspace transformation is one way of reducing computational complexity and sometimes improving the estimation accuracy [37–40]. In this paper, we present a beamspace-based approach for estimating the angular parameters of ID sources. First of all, with generalized array manifold of the ULA, we obtain the beamspace array manifold by performing beamspace transformation on the observed vectors of the overlapping subarrays, and establish the generalized shift invariance structure in beamspace by choosing appropriate beamforming matrix. Then, the total least squares (TLS) method is adopted to estimate the nominal DOAs of ID sources. With the DOA estimates, the angular spread estimates are finally derived from the central moments of the angular distribution. Our approach does not require any spectral search and reduces the dimension of matrix operations, thus it is computationally more attractive than the existing techniques. Simulation results verify the effectiveness of the proposed algorithm.

The paper is organized as follows. In Section 2, we present the array signal model of ID sources and some necessary assumptions. In Section 3, an efficient beamspace-based approach for localization of ID sources is described in detail. Computer simulation results are provided in Section 4, and conclusions are drawn in Section 5.

Notations The superscripts $*$, T, H, $\dagger$ and $'$ denote the conjugate, transpose, conjugate transpose, pseudo-inverse and first-order derivative, respectively. $E\{\cdot\}$ represents the statistical expectation. $\mathbf{I}_P$ stands for the $P\times P$ identity matrix, and $\mathbf{0}_{(M-1)\times 1}$ is the $(M-1)\times 1$ vector of zeros. $[\cdot]_{j,k}$ denotes the (j,k)th entry of a matrix. diag$[\cdot]$ denotes a diagonal matrix and the values in the brackets constitute its diagonal elements. $\delta(\cdot)$ is the Kronecker delta function.

2. Signal model and basic assumptions

Assume that the signals from K narrowband ID sources impinge on a ULA of M sensors. The received signal at the array can be expressed as

$$\mathbf{x}(t)=\sum_{k=1}^{K}s_k(t)\sum_{l=1}^{L_k}\gamma_{k,l}\mathbf{a}(\theta_{k,l}(t))+\mathbf{n}(t) \tag{1}$$

where $t=1,2,\ldots,N$ is the sampling time, and N is the number of snapshots; $s_k(t)$ is the complex-valued signal transmitted by the kth source; L_k is the number of rays inside the kth source and $\gamma_{k,l}(t)$ is the complex-valued gain of the lth ray from the kth source; $\theta_{k,l}(t)\in(-\pi/2,\pi/2)$ is the DOA of the lth ray from the kth source; $\mathbf{n}(t)\in\mathbb{C}^{M\times 1}$ is the complex-valued additive noise vector, whose elements are spatially and temporally zero-mean white Gaussian processes with variance σ_n^2. The array manifold, $\mathbf{a}(\theta_{k,l}(t))\in\mathbb{C}^{M\times 1}$ is the response of the array corresponding to the DOA $\theta_{k,l}(t)$, which is given by

$$\mathbf{a}(\theta_{k,l}(t))=\left[1,e^{j\Delta\sin(\theta_{k,l}(t))},\ldots,e^{j(M-1)\Delta\sin(\theta_{k,l}(t))}\right] \tag{2}$$

where $\Delta=2\pi d/\lambda$, d is the distance between two adjacent sensors, and λ is the wavelength of the impinging signal.

We may represent $\theta_{k,l}(t)$ as

$$\theta_{k,l}(t)=\theta_k+\tilde{\theta}_{k,l}(t) \tag{3}$$

where θ_k is the nominal DOA of the kth source, i.e., the mean of $\theta_{k,l}(t)$; $\tilde{\theta}_{k,l}(t)$ is the corresponding random angular deviation with zero mean and standard deviation σ_k, which is referred to as the angular spread.

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

(i) The angular deviation, $\tilde{\theta}_{k,l}(t)$ is temporally independent and identically distributed (i.i.d.) random variables with covariances:

$$E\{\tilde{\theta}_{k,l}(t)\tilde{\theta}_{\tilde{k},\tilde{l}}(\tilde{t})\}=\sigma_k^2\delta(k-\tilde{k})\delta(l-\tilde{l})\delta(t-\tilde{t}) \tag{4}$$

(ii) The ray gains $\gamma_{k,l}$, $k=1,2,\ldots,K$, $l=1,2,\ldots,L_k$, are temporally white and are independent from ray to ray with zero mean and covariance:

$$E\{\gamma_{k,l}(t)\gamma^*_{\tilde{k},\tilde{l}}(\tilde{t})\}=\frac{\sigma^2_{\gamma_k}}{L_k}\delta(k-\tilde{k})\delta(l-\tilde{l})\delta(t-\tilde{t}) \tag{5}$$

where $\sigma^2_{\gamma_k}$ is the ray gain variance from the kth source.

(iii) The source signals $s_k(t)$, $k=1,2,\ldots,K$, $t=1,2,\ldots,N$, are temporally i.i.d. zero-mean random variables with constant amplitudes and covariance:

$$E\{s_k(t)s^H_{\tilde{k}}(\tilde{t})\}=\sigma^2_{s_k}\delta(k-\tilde{k})\delta(t-\tilde{t}) \tag{6}$$

where $\sigma^2_{s_k}=E\{|s_k(t)|^2\}$ is the signal power of the kth source.

(iv) The source signals, angular deviations, ray gains and noise are mutually uncorrelated.

(v) The number of sources K, is known *a priori* and the number of sensors M is larger than K.