Direction-of-arrival estimation of near-field sources based on compressed symmetric nested array and sparse signal reconstruction

LI Shuang[1], ZHENG Da-qing[1], LIU Wei[1], HU Shun-ren[1], HE Wei[2]
(1. *School of Electrical and Electronic Engineering, Chongqing University of Technology, Chongqing* 400054, *China*;
2. *Key Labarotory of Wireless Sensor Networks and Communication, Shanghai Institute of Microsystem and Information Technology, Chinese Academy of Sciences, Shanghai* 200180, *China*)

Abstract: In this paper, a novel underdetermined direction-of-arrival (DOA) estimation method based on compressed symmetric nested array and sparse signal representation is proposed in the near-field. Firstly, the forth order cumulants are employed to transform the original two-dimensional parameter estimation problem into a one-dimensional one and to obtain the difference co-array of the physical array. Then, in order to further increase the angular resolution and reduce the estimate error, the received signals of the virtual array are sparsely represented in spatial domain. Finally, the DOAs of the sources are founded through the use of the L1-regularized least square method. Compared to the existing methods, the proposed approach can process more sources and have lower variance and higher resolution. Simulation results are given to demonstrate the effectiveness and efficiency of the proposed method.

Key words: array signal processing; underdetermined direction-of-arrival estimation; near-field; sparse signal recovery; fourth order cumulant

0 Introduction

Source localization using sensor arrays plays an important role in many applications such as radar, sonar, wireless sensor networks, wireless communication and so on. According to the distance between the sources and the reference sensor of an array, source localization can be categorized into two types: far-field and near-field. In the far-field, the signal at the array can be approximated as plane wave and only the direction-of-arrival (DOA) estimation is required. However, the wavefront of the signal must be characterized by both azimuth and range in the near-field, where a joint azimuth and range estimation should be conducted. Therefore, the performances of those source localization methods making a far-field assumption will severely degrade in the near-field.

In recent years, many methods were proposed to deal with the near-field source localization problem. Through the use of a symmetric array and generalized ESPRIT method, Zhi and Chia[1] presented a source localization method, which transform the problem into a one-dimensional one. However, it suffers from aperture loss, i.e., only N sources can be processed by using a symmetric array with $2N+1$ sensors[2]. Based on cumulants, Liang and Liu[3] proposed the Two-stage MUSIC method to localize both near-field and far-field sources, which alleviates the aperture loss to some extent. In recent years, owing to the superior performance of DOA estimation methods in the far-field such as ℓ_1-SVD [4], the sparse-signal- recovery-based source localization methods were extended to the near-field case[5-9], exhibiting some advantages including high resolution, improved robustness to noise and to a limited number of snapshots. Meanwhile, some non-uniform linear arrays were exploited in order to increase the aperture of the array[10-11]. As a typical non-uniform array, Nested array[12] can be employed to improve degrees of freedom of the physical array. However, it only works in the far-field. In 2016, by utilizing a novel non-uniform linear array named compressed symmetric nested array, the authors presented a novel DOA estimation method which could identify more sources than sensors in the near-field[13]. However, only half difference co-array of the physical array is employed when constructing the covariance matrix of the signal observed by the virtual co-array.

In this paper, based on compressed symmetric nested array and sparse signal reconstruction, a new

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作者简介：李双(1986－), 男, 四川南充人, 博士, 讲师, 研究方向为阵列信号处理及其应用。
通讯作者：李双, E-mail: lis@cqut.edu.cn

source localization method is proposed in the near-field. The degrees of freedom are further increased by exploiting sparse signal reconstruction so that higher resolution can be achieved. Compared to the existing methods, the proposed method has a superior performance including higher resolution and lower variance.

The rest of the paper is organized as follows. Section 2 describes the DOA estimation model in the near-field. How the proposed method works is given in Section 3, which is followed by simulation results in section 4. Section 5 concludes the paper.

1 Data model

Consider this scenario depicted in Fig.1 that K narrowband sources located in the Fresnel zone impinge onto a non-uniform symmetric linear array with $N=2u$ elements (The number of sensors is assumed to be even, however, the proposed method also works well for odd case). All elements are assumed to be located at the underlying grid with a minimum spacing d . The location vector of the sensors is given as $\{l_{-u}, l_{-u+1}, \cdots, l_u\}$. Then the observed signal of the ith sensor can be expressed as

$$x_i(t)=\sum_{k=1}^{K} e^{j\frac{2\pi}{\lambda}(r_{ik}-r_k)} s_k(t)+n_i(t),\quad i=-u,-u+1,\cdots,u;\ t=1,2,\cdots,T \tag{1}$$

where $s_k(t)$ denotes the kth source, $n_i(t)$ represents the noise received by the ith sensor, λ refers to the wavelength of the sources, T denotes the number of snapshots, r_k stands for the distance between the kth source and the reference sensor of the array and r_{ik} is the distance from the ith sensor to the kth source.

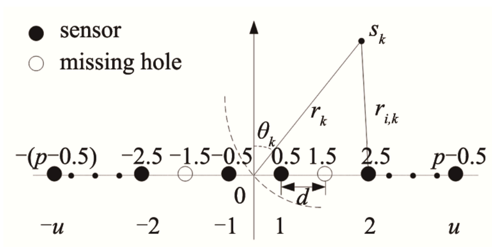

Fig.1　Array geometry in the near-field

According to Fig.1, we have

$$r_{ik}=\sqrt{r_k^2+l_i^2 d^2-2l_i d r_k \sin\theta_k} \tag{2}$$

Through the use of second order Taylor expansion of (2), we can obtain the so-called Fresnel approximation

$$r_{ik}\approx r_k-l_i d\sin\theta_k+\frac{l_i^2 d^2}{r_k}\cos^2\theta_k \tag{3}$$

Substituting (3) into (1), we obtain

$$x_i(t)=\sum_{k=1}^{K} e^{j(l_i\omega_k+l_i^2\varphi_k)} s_k(t)+n_i(t),\ t=1,2,\cdots,T \tag{4}$$

where

$$\omega_k=-\frac{2\pi d}{\lambda}\sin\theta_k \tag{5}$$

and

$$\varphi_k=\frac{\pi d^2}{\lambda r_k}\cos^2\theta_k \tag{6}$$

Let $\boldsymbol{x}(t)=[x_{-u}(t), x_{-u+1}(t),\cdots,x_u(t)]^T$, $\boldsymbol{s}(t)=[s_1(t), s_2(t),\cdots,s_K(t)]^T$ and $\boldsymbol{n}(t)=[n_{-u}(t), n_{-u+1}(t),\cdots,n_u(t)]^T$ denote the observed signal vector, the source vector and the received noise vector, respectively, then (4) can be rewritten in a vector form as

$$\boldsymbol{x}(t)=\boldsymbol{A}(\boldsymbol{r},\boldsymbol{\theta})\boldsymbol{s}(t)+\boldsymbol{n}(t) \tag{7}$$

where $\boldsymbol{r}=[r_1, r_2,\cdots,r_K]^T$ and $\boldsymbol{\theta}=[\theta_1,\theta_2,\cdots,\theta_K]^T$ denote the range and DOA vector of the sources, $\boldsymbol{A}(\boldsymbol{r},\boldsymbol{\theta})=[\boldsymbol{a}(r_1,\theta_1),\boldsymbol{a}(r_2,\theta_2),\cdots\boldsymbol{a}(r_k,\theta_k)]$ is the array manifold matrix and $\boldsymbol{a}(r_k,\theta_k)$ is the steering vector, whose ith entry is $e^{j(l_i\omega_k+l_i^2\varphi_k)}$.

Since we only focus on the DOA estimation of the sources, the source localization problem is: given the observed vector $\boldsymbol{x}(t)$ for $t=1,2,\cdots,T$ to find the DOA vector $\boldsymbol{\theta}$.

To simplify the derivation, we make some assumptions as follows.

(A1) - the sources are non-Gaussian, and independent with each other.

(A2) - the noises are Gaussian, either white or colored.

(A3) - the noises are independent of the sources; and

(A4) -to avoid angular ambiguous, the underlying grid spacing d satisfies that $d\le\lambda/4$.

2 The proposed method

2.1 Nested array and compressed symmetric nested array(CSNA)

A nested array with $N=N_1+N_2$ sensors is basically a concatenation of two uniform linear subarrays, an inner one with N_1 elements located at $\{nd, n=1,2,\cdots,N_1\}$ and an outer one with N_2 located in

$\{n(N_1+1)d, n=1,2,\cdots,N_2\}$ [12]. It has been verified that the difference co-array of a nested array is a uniform linear array with $2N_2(N_1+1)-1$ elements. A compressed symmetric nested array is composed of three uniform linear subarrays, an inner one with N_1+1 elements located at $\{(n\text{-}(N_1+1)/2)d, n=1,2,\cdots,N_1+1\}$ and two outer ones symmetrically located at $\{(n-1/2)(N_1+1)d, n=2,\cdots,N_2\}$ and $\{(n+1/2)(N_1+1)d, n=-N_2,-N_2+1,\cdots,-2\}$ [13]. In other words, compressed symmetric nested array consists of the remaining elements by getting rid of some ones from two identical nested arrays. Fig.2 gives an example of nested array and compressed symmetric nested array. Apparently, the difference co-arrays of the two physical arrays in Fig. 2 contain the same ULA with 23 elements.

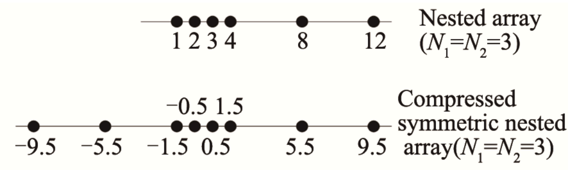

Fig.2 Nested array and compressed symmetric nested array

2.2 The proposed method

To acquire the difference co-array of a physical array, we exploit the fourth order cumulants of the received signals, which can be defined as

$$\begin{aligned}&\mathrm{cum}(x_m(t),x_n^*(t),x_p(t),x_q^*(t))=E\{x_m(t)x_n^*(t)x_p(t)x_q^*(t)\}-\\&E\{x_m(t)x_n^*(t)\}E\{x_p(t)x_q^*(t)\}-E\{x_m(t)x_p(t)\}E\{x_n^*(t)x_q^*(t)\}-\\&E\{x_m(t)x_q^*(t)\}E\{x_n^*(t)x_p(t)\}, m,n,p,q\in(-u,-1)\cup(1,u)\end{aligned} \tag{8}$$

Under the assumptions (A2) and (A3), by substituting (4) into (8) and employing the properties of cumulants, we have.

$$\begin{aligned}&cum(x_m(t),x_n^*(t),x_p(t),x_q^*(t))=\\&\sum_{k=1}^{K}\mathrm{e}^{\mathrm{j}[(l_m-l_n+l_p-l_q)\omega_k+(l_m^2-l_n^2+l_p^2-l_q^2)\varphi_k]}c_{4,sk}\end{aligned} \tag{9}$$

where $c_{4,sk}=cum(s_k(t),s_k^*(t),s_k(t),s_k^*(t))$ denotes the kurtosis of the kth source signal. Note that the noise term disappears since the forth order cumulant of Gaussian noise is zero. Let $l_n=-l_m$ and $l_p=-l_q$ which means $n=-m$ and $p=-q$, then substituting them into (9), we obtain

$$\begin{aligned}&cum(x_m(t),x_{-m}^*(t),x_{-q}(t),x_q^*(t))=\\&\sum_{k=1}^{K}\mathrm{e}^{\mathrm{j}2(l_m-l_q)\omega_k}c_{4,sk}, m,q\in(-u,-1)\cup(1,u)\end{aligned} \tag{10}$$

Actually, the right side of (10) acts as the correlation between the mth and the qth sensors of a virtual array in the far-field, which is just the difference co-array of the real array. In the above derivation, $n=-m$ and $p=-q$ are required so the sensors of the physical array must be placed in a symmetric way. Therefore, the nested arrays cannot be exploited directly. Here, we take advantage of the compressed symmetric nested array(CSNA). We assume the CSNA has N_1+2N_2-1 elements, where N_1+1 and N_2-1 denotes the number of sensors in the inner and each outer subarray, respectively. It has been shown that the difference co-array of the CSNA and a nested array with N_1+N_2 elements contains the same ULA with $2N_2(N_1+1)-1$ elements when N_1 and N_2 represent the number of sensors in each level of the nested array.

When such a CSNA with N_1+2N_2-1 elements is utilized and only the contained ULA in the difference coarray of the CSNA is considered, l_m-l_q will vary from $-N_v$ to N_v, where $N_v=N_2(N_1+1)-1$. Therefore, we can obtain such a vector $\boldsymbol{c}$ from (10) that

$$\boldsymbol{c}=\boldsymbol{A}_\omega\boldsymbol{c}_s \tag{11}$$

where $\boldsymbol{c}_s=[c_{4,s1},c_{4,s2},\cdots,c_{4,sK}]^{\mathrm{T}}\in C^{K\times1}$, $\boldsymbol{A}_\omega=[\boldsymbol{a}_\omega(\omega_1), \boldsymbol{a}_\omega(\omega_2),\cdots,\boldsymbol{a}_\omega(\omega_k)]\in C^{(2N_v+1)\times K}$, $\boldsymbol{a}_\omega(\omega_k)=[\exp(-\mathrm{j}2N_v\omega_k), \exp(-\mathrm{j}2(N_v-1)\omega_k,\cdots,\exp(\mathrm{j}2N_v\omega_k)]^{\mathrm{T}}$ and $\boldsymbol{c}\in\mathbb{C}^{(2N_v+1)\times1}$, whose ith element is $cum(x_m(t),x_{-m}^*(t),x_{-q}(t),x_q^*(t))$, in which m and q satisfy $l_m-l_q=i-1-N_v$.

Here, we exploit sparse signal reconstruction to perform DOA estimation on the sparse representation of c. We define a set $\boldsymbol{\Theta}=[\theta_1,\theta_2,\cdots,\theta_{N_\theta}]$ to refer to the sample grid of the DOA of the potential sources and then construct an overcomplete basis $\bar{\boldsymbol{A}}=[\boldsymbol{a}_\omega(\bar{\omega}_1), \boldsymbol{a}_\omega(\bar{\omega}_2),\cdots,\boldsymbol{a}_\omega(\bar{\omega}_{N_\theta})]$, where $\bar{\omega}_k=(2\pi d\sin\bar{\theta}_k)/\lambda$. The sparse signal can be represented by a sparse vector $\boldsymbol{p}$, whose ith entry is $c_{4,sk}$ if the source $s_k(t)$ happens to come from the direction $\bar{\theta}_i$ and zero otherwise. The sparse vector $\boldsymbol{p}$ serves as the spatial angular spectrum, i.e., the dominant peaks correspond to the true directions of the sources. Generally speaking, the number of potential sources should be far more than the number of real sources and that of sensors in virtual array, i.e., $N_\theta\gg K$ and $\mathrm{N}_\theta\gg 2N_v+1$. Then, the grid-based model can be expressed as

$$\boldsymbol{c}=\bar{\boldsymbol{A}}_\omega\boldsymbol{p} \tag{12}$$

Subsequently, the DOA estimation can be performed by solving the following ℓ_1-regularized least square problem

$$\boldsymbol{\theta}=\arg\min_{\theta}(1-h)\left\|\boldsymbol{c}-\bar{\boldsymbol{A}}\boldsymbol{p}\right\|_2^2+h\left\|\boldsymbol{c}\right\|_1 \tag{13}$$

where h is a regularization parameter, which balances data-fidelity with sparsity. It plays an crucial role while finding the sparse solution. A small h emphasizes the role of ℓ_2-term, which may result in the occurrence of some spurious peaks. On the contrary, a large h emphasizes the role of ℓ_1-term, which may cause some peaks to disappear. Here, just like the method in [5], we make use of the method of L-curve[5] to find a proper value for the parameter h. The L-curve is a useful and convenient graphical tool to exhibit the trade-off between the size of regularized solution and its fit to the given data.

After choosing the proper regulation parameter, the CVX toolbox[14] can be utilized to find the spatial spectrum $\boldsymbol{p}$ by solving the issue in (13). Then the DOA can be obtained by finding the K largest peaks of the spatial spectrum.

Remark 1: regarding the number of sources that the proposed method can process, we give a theorem to explain it.

Lemma 1 Consider a multiple measurement vectors problem of $\boldsymbol{\Phi Y}=\boldsymbol{Z}$, where $\boldsymbol{\Phi}$, $\boldsymbol{Y}$, and $\boldsymbol{Z}$ denote the measured matrix, the sparse matrix and the observed matrix, respectively. With the assumption that any b columns of $\boldsymbol{\Phi}$ are linearly independent and $rank(\boldsymbol{Z})=L<b$, a solution with number of nonzero entries g, where $g\le g_u=\lceil(b+L)/2\rceil-1$, is unique (where $\lceil\ \rceil$ denotes the ceiling operation)[15]. In the proposed method, $L=rank(\boldsymbol{c})=1$, $b=2N_v+1$. Therefore, the maximum number of sources that the proposed method can identify is $g_u=N_v$, which is equivalent to that of the method in [13].

Remark 2: With regard to the computational complexity, the computational cost of the two-stage MUSIC method is mainly in computation of cumulants and eigenvalue decomposition, whose cost is $O(TN^4)+O(N^3)$. The main cost of the method in [13] is $O(TN^4)+O((N^2/8+N/2)^3)$ ($N=2k$ is assumed, where k is an integer), which is related to the number of the sensors in the difference co-array of the physical array. The proposed method involves computation of forth order cumulants and sparse signal reconstruction. Therefore, the computational cost is $O(TN^4)+O(N_\theta^3)$, which is somewhat higher than two-stage MUSIC and the method in [13]. However, through the use of the proposed method, the benefits we obtain include higher resolution and lower errors, which will be verified by numerical simulation.

Remark 3: As to array geometry, since the proposed method only requires the array is symmetric, it will work well when the number of the array is odd as we mentioned before.

3 Simulation results

In this section, several numerical experiments are presented to demonstrate the effectiveness and efficiency of the proposed method. We compare our method to the two-stage MUSIC method[3], which is based on uniform linear array and MUSIC method, and the method in [13], which is based on compressed symmetric nested array and MUSIC method. In the following experiments, we all consider this case in which two near-field sources are received by two sensor arrays of 8 elements, which are a CSNA located in $\{(-9.5\ -5.5\ -1.5\ -0.5\ 0.5\ 1.5\ 5.5\ 9.5)d\}$ and a ULA. We assume the minimum underlying grid of the CSNA is equivalent to the intersensor spacing of the ULA. The sources are modeled as exponential process while the noises are Gaussian and white.

3.1 Spatial spectra

First of all, we compare the abovementioned methods in terms of spatial spectrum. Since the two-stage MUSIC method cannot identify more sources than sensors, we consider a overdetermined case where two sources are closely placed at $(-40°,12\lambda)$ and $(-46°,15\lambda)$. Fig.3 depicts the spatial angular spectra for the three methods with $SNR=10$ dB and $T=2\,000$. The real DOAs are marked by the circles. It can be clearly discovered that our proposed method can well identify the two sources that the two other methods cannot process.

Since the proposed method and the method in [13] can process 11 sources by exploiting compressed symmetric nested array of 8 elements, then we consider a underdetermined DOA estimation case in which the 11 sources uniformly located in the directions $[-60°,\ 60°]$ impinge onto this non-uniform linear array. The spatial spectra of the two methods are given in Fig.4. In this experiment, $SNR=20$ dB and $T=10\,000$. It has been shown that both the two methods can detect all the sources. Moreover, the proposed method has sharper peaks than the method in [13].

Hence, according to the two figures, we can draw a conclusion that our method achieves higher resolution compared to the other two methods, which will be verified in the subsequent section. Besides, both the proposed method and the method in[13] can identify more sources than sensors.

3.2 **RMSE**

In this subsection, the RMSE of the above three methods are evaluated. The RMSE is defined as

$$\mathrm{RMSE}=\sqrt{\frac{1}{KN_{mc}}\sum_{i=1}^{N_{mc}}\sum_{k=1}^{K}(\hat{\theta}_{k,i}-\theta_{k,i})}$$

where N_{mc} denotes the number of Monte Carlo trials, $\hat{\theta}_{k,i}$ and $\theta_{k,i}$ represent the kth estimate and real DOA in the ith run, respectively.

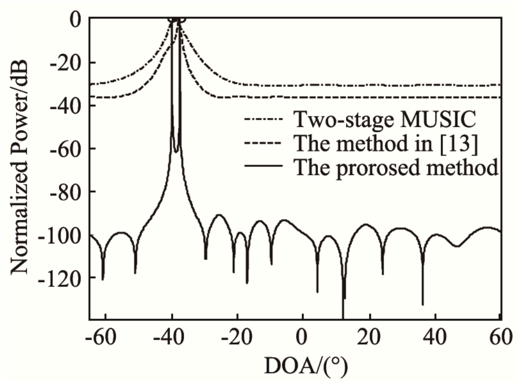

Fig.3 Angular spatial spectrum for two closely spaced signals

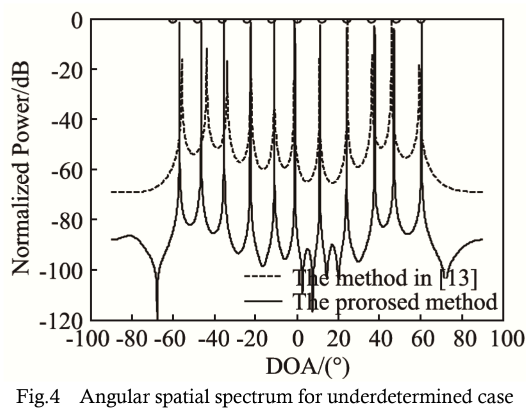

Fig.4 Angular spatial spectrum for underdetermined case

To fairly compare RMSE of the three methods, the positions of the two sources are set as $\{-25.4°, 21\lambda\}$ and $\{14.7°, 13\lambda\}$. The SNR varies from 8 dB to 20 dB with a step of 2 dB. The RMSE of the three methods as a function of SNR are demonstrated in Fig.4 by taking the average of 200 Monte Carlo trials. According to Fig.5, the proposed method has a lower RMSE compared with the two other methods and the method in [13] achieves a lower variance in low SNR than Two-stage MUSIC.

Then we keep all the parameters the same as the last experiment except that the SNR is fixed 10dB and make a comparison to the three methods when the number of snapshots ranges from 200 to 4 000. Fig.6 illustrates RMSE of the three methods with respect to the number of snapshots. It can be noted that the proposed method has a higher RMSE when the number of snapshot is relatively small while lower variance can be obtained by the proposed method when a great number of snapshots are available compared to the other methods.

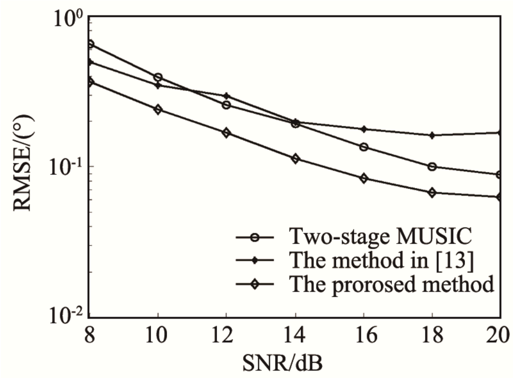

Fig.5 RMSE versus SNR

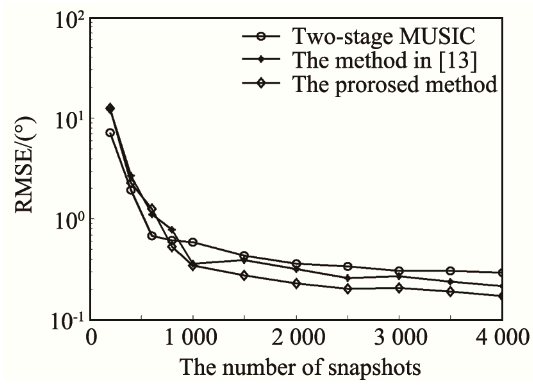

Fig.6 RMSE as a function of the number of snapshot

3.3 **Resolution**

Now, we investigate the resolution ability of the three methods regarding the SNR and the number of snapshots respectively. By a definition in [15], two closely spaced signals located in $\{\theta_1, \theta_2\}$ can be identified if the two sources satisfy the conditions that both $|\hat{\theta}_{i,1}-\theta_1|$ and $|\hat{\theta}_{i,2}-\theta_2|$ are smaller than $|\theta_1-\theta_2|/2$, where $\hat{\theta}_{i,j}$ stands for the DOA of the jth signal in the ith run. Two sources radiated from $\{-3°, 21\lambda\}$ and $\{3°, 13\lambda\}$ are considered in this test. The resolution ability with respect to the SNR for the three methods is depicted in Fig.7 with 200 Monte Carlo trials by changing the SNR from 0 dB to 20 dB with a step of 1 dB. It can be clearly discovered that the proposed method achieves the higher resolution than the other two methods. The reason is that both compressed symmetric nested array and the approach of sparse signal recovery are exploited in the proposed method.

Then, the resolution probabilities of the three methods are investigated for different numbers of snapshots, which varies from 200 to 2 000 with a step of 300. How the resolution ability changing with the number of snapshots is exhibited in Fig.8. It can be obviously noted that the proposed method outperforms the other two methods.

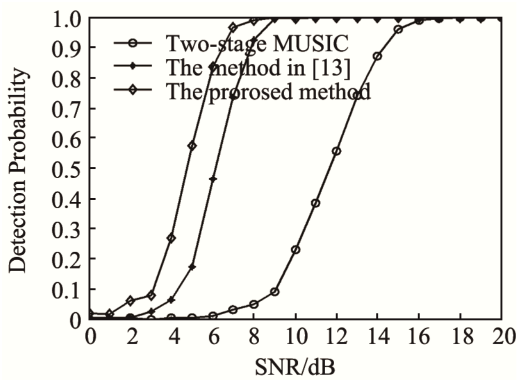

Fig.7 Resolution ability with respect to SNR

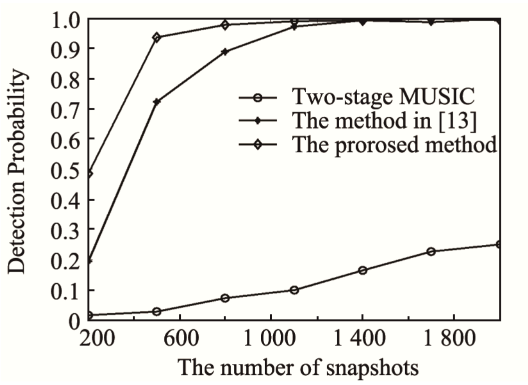

Fig.8 Resolution ability with respect to the number of snapshots

4 Conclusions

In this paper, a novel DOA estimation method based on compressed symmetric nested array and sparse signal recovery is proposed in the near-field. The proposed method has several advantages. First, it can process more sources than sensors. Furthermore, compared to the existing methods, the proposed method can obtain higher resolution and lower variance. Future research will involve the design of more efficient array for near-field source localization.

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压缩对称嵌套阵列和稀疏信号重构的近场目标方位估计

李 双[1]，郑大青[1]，刘 伟[1]，胡顺仁[1]，何 为[2]
(1. 重庆理工大学电气与电子工程学院，重庆 400054；
2. 中国科学院上海微系统与信息技术研究所无线传感网与通信重点实验室，上海 200180)

摘要：针对现有近场源估计算法中近场源数量受限于阵元数的问题，提出了一种基于稀疏对称嵌套阵列和稀疏信号重构的近场欠定波达方向估计方法。首先利用四阶累积量，将二维空间参数估计问题转化为一维参数估计问题，同时得到差分阵列；为了进一步提高估计分辨率与减少估计误差，对虚拟阵列的接收信号在空间域进行稀疏表示；最后通过 L1 范数最小二乘法得到目标源的波达方向。相较于现有算法，该方法可以估计更多的目标源，并且有更低的均方误差与更高的分辨率。实验仿真验证了算法的有效性与优越性。

关键词：阵列信号处理；欠定波达方向估计；近场；稀疏信号重构；四阶累积量
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向宁博士获世界人才中心授予“终身成就奖”并入选《世界著名传记和名人录》

2018 年 2 月 22 日，世界人才中心宣布授予向宁博士“终身成就奖”，并将其列入《世界著名传记和名人录》，以表彰其在专业领域的卓著研究成就和杰出的领导才能。

向宁博士早年毕业于天津大学电子工程学院，后获德国鲁尔大学电子工程硕士和博士学位。

自 2003 年以来，向宁博士一直担任美国伦斯勒理工学院(Rensselaer Polytechnic Institute)建筑学院教授。此前在美国密西西比大学国家物理声学中心任研究员，并在德国亚琛 HEAD acoustics 高科技公司等处任职多年。他的研究领域包括建筑声学、声信号处理和贝叶斯推论在声学中的应用等。向宁博士的论文和专著颇丰，他主编的《建筑声学手册》(英文版，J. Ross 出版社)于 2017 年最新出版，获业界赞誉。

因向宁博士在建筑声学领域的杰出贡献，2014 年美国声学学会授予向宁博士赛宾奖(the Wallace Clement Sabine Award)。向宁博士是 1957 年初次颁发该奖以来首位获此殊荣的华裔科学家，也是第 16 位奖章获得者。

向宁博士长期以来一直担任美国声学学会学报(JASA)的副主编。近年来，向宁博士经常回国讲学，与国内一些高校和研究机构保持着密切的联系。

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