A FAST DIRECT SOURCE LOCALIZATION APPROACH FOR ACOUSTIC SENSOR ARRAY

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ABSTRACT

We present a novel Fast Direct Source Localization (FDSL) approach for acoustic isotropic sensor array applications. Unlike previous approximate maximum likelihood (AML) approach, the proposed FDSL focuses on the phase shift caused by time delays among sensors and obtains an analytical result without exhaustive search for all the possible locations. Using this phase shift model, conventional phase uncertainty problem can be solved by a light-weight linear search in the limited phase space, which greatly reduces the computational complexity of array processing. Theoretical analysis of the FDSL has been proposed and compared with the Cramér Rao Bound (CRB) of the AML approach. Simulations using real bird call data validate the advantage of proposed method.

***Index Terms*—** Source Localization, Sensor Array, Direction of Arrival (DOA).

1. INTRODUCTION

Source localization using sensor array has been one of the key problem in many applications such as radar, sonar, acoustic tracking etc. [1] [2] [3]. For the past few decades, a wide variety of source localization algorithms have been proposed [4].

For low-cost embedded systems, reducing the complexity of array processing is the key to near real-time localization updating. For the AML [5] [6] approach, normal 2D exhaustive search needs to cover all the possible locations via many iterations. Similarly, although the result of sparsity signal reconstruction (SSR) [7] can be obtained in one step, the large number of variables (number of grid) in sparse reconstruction require much computational resource. In summary, the reason for exhaustive search and sparse signal reconstruction is that the location parameters are hidden in the complex exponential part of the array data spectrum. Thus the 2π periodicity makes it difficult to find the unique connection from complex array data spectrum to location parameters (which can be called the ambiguity problem in array processing).

In this paper, we focus on the phase shift among sensor nodes rather than the complex exponential values of phase shifts and find an analytical solution for source location estimation problem. We call this approach a Fast Direct Source Localization (FDSL) estimation. Using the FDSL approach, the source localization is formulated as a matrix calculation. The array geometry information helps to transform the exhaustive search and optimization search to lighted-weight linear search in limited phase space. The main contributions are:
1) A novel Fast Direct Source Localization (FDSL) estimation scheme is proposed, which provides analytical solutions with greatly reduced complexity;
2) The error covariance of the FDSL is provided and compared with the Cramer Rao Bound of the traditional AML approach;
3) Simulation using real data validates the feasibility of our approach and shows its superior performance.

This paper is organized as follows. In Section 2, the array signal model and conventional array processing are introduced. Then the problem formulation of the FDSL is explored in Section 3. In section 4, we provide some theoretic analysis of the FDSL approach. In Section 5, we provide some simulation results that show the advantages of the proposed algorithm. Finally, we conclude our work in Section 6.

2. ARRAY SIGNAL MODEL AND PROCESSING

2.1. Array Signal Model

Consider a source localization system with H isotropic sensor arrays [8] and each sensor array is equipped with M omnidirectional microphones collecting signals from one source in the far field. The data received by the mth microphone of the hth array is given by

$$x_{hm}(t) = s_h\left(t - \tau_{hm}(\mathbf{r}_s)\right) + n_{hm}(t), t = 0, \ldots, N-1, \quad (1)$$

in which $s_h(t)$ is a wideband signal of the source in the centroid of the hth array, $\tau_{hm}(\mathbf{r}_s)$ is the time delay of the source between the mth sensor and the centriod of the hth array, $\mathbf{r}_s$ is the position of the source, $n_{hm}(t)$ is the zero-mean white Gaussian noise with variance σ^2, and N is the number of signal samples. For simplification, we denote (h, m)th as the mth sensor of the hth array.

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We assume that the position of the (h, m)th sensor in the Cartesian coordinate system is $\mathbf{r}_{hm} = [x_{hm}, y_{hm}]^T$ and the array centroid is $[0, 0]^T$, the corresponding time delay of one source between the (h, m)th sensor and the array centroid is given by

$$\tau_{hm} = \frac{1}{c}\mathbf{r}_{hm}^T\mathbf{a}_h, \tag{2}$$

where c is the propagation speed of acoustic signal, $\mathbf{a}_h = (\mathbf{r}_s - \mathbf{r}_h) / \|\mathbf{r}_s - \mathbf{r}_h\|$ is defined as the unit vector of the source observed in the hth array. After dividing the time domain signal into multiple frames and employing the Discrete Fourier Transform (DFT) on each frame, the array data spectrum $\mathbf{X}_h(k) = [X_{h1}(k), X_{h2}(k), \cdots, X_{hM}(k)]^T$ in the hth array at frequency f_k can be given by

$$\mathbf{X}_h(k) = s_h(k)\mathbf{d}_h(\mathbf{r}, k) + \mathbf{n}_h(k), k = 0, \dots, N/2 - 1. \tag{3}$$

where $\mathbf{d}_h(k) = \left[e^{(-j\omega_k\tau_{h1})}, e^{(-j\omega_k\tau_{h2})}, \cdots, e^{(-j\omega_k\tau_{hM})}\right]^T$ is the steering vector of the source, $s_h(k)$ is the corresponding source spectrum, and $\mathbf{n}_h(k)$ is the gaussian white noise.

2.2. AML Array Processing

The AML approach calculates the likelihood function $J(\mathbf{r})$ over all the possible locations, then returns the most likely location. After ignoring some irrelevant constant terms, the maximum likelihood estimation of the source location is given by

$$\max_{\mathbf{r}} J(\mathbf{r}) = \min_{\mathbf{r}} \sum_{k=1}^{K}\sum_{h=1}^{H} ||\mathbf{X}_h(k) - \mathbf{d}_h(\mathbf{r}, k)\mathbf{S}_h(k)||^2, \tag{4}$$

where K is the number of active frequencies that are chosen for array processing. Consider the brute-force search of the AML algorithm, the complexity of the AML algorithm is determined by size of angle search space.

3. FAST SOURCE LOCALZATION

3.1. Problem Formulation

Recall Eq.(2), the phase shift between the (h, m)th sensor and the array centroid at frequency f_k is

$$P_{hmc}^{(k)} = 2\pi f_k \tau_{hm} = \frac{2\pi f_k}{c}\mathbf{r}_{hm}^T\mathbf{a}_h^{(k)}. \tag{5}$$

Then the phase shifts vector $\mathbf{P}_{hc}^{(k)} = [P_{h1c}(k), \cdots, P_{hMc}(k)]$ of the hth array is given by

$$\mathbf{P}_{hc}^{(k)} = \frac{2\pi f_k}{c}\mathbf{R}_h\mathbf{a}_h^{(k)}, \tag{6}$$

in which $\boldsymbol{R}_h = [\mathbf{r}_{h1}, \mathbf{r}_{h2}, \dots, \mathbf{r}_{hM}]^T$ is the array position matrix. We assume all the H isotropic arrays have the same geometry in their own coordinate systems ($\mathbf{R}_1 = \cdots = \mathbf{R}_H = \mathbf{R}$, $\mathbf{R}^\mathbf{T}\mathbf{R} = \kappa\mathbf{I}$). The unit vector can be obtained by

$$\mathbf{a}_h^{(k)} = \frac{c}{2\pi f_k}\left(\mathbf{R}_h^T\mathbf{R}_h\right)^{-1}\mathbf{R}_h^T\mathbf{P}_{hc}^{(k)} = \frac{c}{2\pi\kappa f_k}\mathbf{R}_h^T\mathbf{P}_{hc}^{(k)}. \tag{7}$$

Based on the unit vector of H sensors, the triangulation based source localization is:

$$\frac{y_s - y_h}{x_s - x_h} = \frac{\mathbf{a}_h^{(k)}(2)}{\mathbf{a}_h^{(k)}(1)}, h = 1, 2, ..., H, \tag{8}$$

or in matrix format:

$$\mathbf{A}(k)\mathbf{r}_s = \mathbf{F}(k), \tag{9}$$

where $\mathbf{A}(k) = [\mathbf{a}_1, \mathbf{a}_2, \cdots, \mathbf{a}_H]^T\,\mathbf{T}$, $\mathbf{F}(k) = [\mathbf{a}_1\mathbf{T}\mathbf{r}_1, \mathbf{a}_1\mathbf{T}\mathbf{r}_2, \cdots, \mathbf{a}_1\mathbf{T}\mathbf{r}_H]^T$, $\mathbf{a}_h = \sum_{k=1}^K \omega_k\mathbf{a}_h^{(k)} / \sum_{k=1}^K \omega_k$, ω_k is the summation weight of different frequency and $\mathbf{T} = \left[\begin{smallmatrix}0 & 1\\ -1 & 0\end{smallmatrix}\right]$ is a steering vector that rearranges $\mathbf{a}_h$. Then the least square solution is

$$\mathbf{r}_s = (\mathbf{U})^{-1}\mathbf{V}, \tag{10}$$

where $\mathbf{U} = \mathbf{T}\sum_{h=1}^H \mathbf{a}_h\mathbf{a}_h^T\mathbf{T}^T$, $\mathbf{V} = \sum_{h=1}^H \left(\mathbf{T}\mathbf{a}_h\mathbf{a}_h^T\mathbf{T}^T\mathbf{r}_h\right)$.

3.2. Phase Measurement and Uncertainty

The 2π periodicity of $\exp(-j\omega_k\tau_{hm})$ makes it difficult to find the right τ_{hm} from the cross spectral $X_{hm}(k)X_{h0}^*(k)$ between the (h, m)th sensor and the hth array centroid. To solve this issue, a fast phase search approach is proposed that finds the right phase shift from the array data spectrum. In this paper, only single source localization is considered. However, this FDSL approach also works for multiple sources case when the orthogonal projection technology [5] is introduced. To clarify the heart of the fast phase search approach, we only focus on the single source case in this paper.

3.2.1. Phase Measurement

Recall Eq. (5), $P_{hmc}^{(k)}$ is defined as the phase difference between the (h, m)th sensor and the array centroid at frequency f_k. In this section, we only focus on single sensor array, thus the index h is ignored in all notations. Consider all M sensors of an array, the phase shift vector is

$$\mathbf{P}_c^{(k)} = \left[P_{1c}^{(k)}, P_{2c}^{(k)}, \cdots, P_{Mc}^{(k)}\right]^T. \tag{11}$$

The array data spectrum in Eq. 3 is consistent with the steering vector, so the observed phase shift $P_{mc}^{(k)}$ between the mth and the array centroid can be given by

$$\tilde{P}_{mc}^{(k)} = \mathrm{atan2}\left(\mathrm{Im}(\mathrm{X_{hm}(k)X_{h0}^*(k)}), \mathrm{Re}(\mathrm{X_{hm}(k)X_{h0}^*(k)})\right), \tag{12}$$

where $\mathrm{atan2(b, a)}$ calculates the angle of $a + ib$. Because of the 2π periodicity of $\mathrm{atan2(b, a)}$, the real phase shift $P_{mc}^{(k)}$ and the observed phase shift $\tilde{P}_{mc}^{(k)}$ satisfy

$$P_{mc}^{(k)} = \tilde{P}_{mc}^{(k)} + 2\pi I_k, \tag{13}$$

where I_k is an unknown integer number. On condition that the array centroid is not equipped with a sensor, the equivalent $\mathbf{P}_c^{(k)}$ can be obtained by

$$\mathbf{P}_c^{(k)} = \left(\mathbf{I} - \frac{\mathbf{1}_{M\times M}}{M}\right)\mathbf{P}_m^{(k)}, \tag{14}$$

where $\mathbf{P}_m^{(k)} = [P_{1m}(k), P_{2m}(k), \cdots, P_{Mm}(k)]$ is the phase shift vector with respect to the mth sensor. This is because $\sum_{m=1}^{M} P_{mc}^{(k)} = 2\pi f_k/c \sum_{m=1}^{M} \mathbf{r}_m^T \mathbf{a}^{(k)} = 0$.

3.2.2. *Phase Search Formulation*

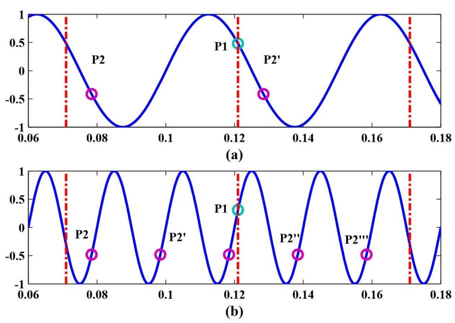

Fig. 1. (a) Phase search of low frequency, (b) Phase search of high frequency

Based on the observed phase shift, the uncertainty of the real phase shift in Eq. 13 should be solved. Fig. 1 shows the uncertainty of phase shift, suppose the largest distance D is smaller than the wavelength (as shown in Fig.1.a), then the corresponding phase shift should be smaller than 2π. This condition is equivalent to $f_k \leq \frac{c}{D} = f_{Low}$. Frequencies less than f_{Low} have smaller phase shifts than 2π.

In this case, the possible alternative phase shifts between the nth and the mth sensors are

$$P_{nm}^{(k)} = \begin{cases} \tilde{P}_{nm}^{(k)} \\ \tilde{P}_{nm}^{(k)} - 2\pi \mathrm{sign}(\tilde{P}_{nm}^{(k)}) \end{cases}. \tag{15}$$

Consider each $P_{mn}^{(k)}$ has 2 alternatives, the total alternative number of $\mathbf{P}_m^{(k)}$ is 2^{M-1}. We further divide this 2^{M-1} alternatives into M cases, in which each sensor is assumed to be nearest to the source and has the smallest phase. If the mth sensor has the smallest phase, $P_{nm}^{(k)}(n = 1, 2, \cdots, M, n \neq m)$ should only be positive and the negative one can be excluded from Eq. 15. Since each case has only one possible $\mathbf{P}_m^{(k)}$, the total number of of all the M cases can be reduced to

$$\begin{aligned} &\mathbf{P}_m^{(k)} = \tilde{\mathbf{P}}_m^{(k)} + \pi \mathrm{sign}(\tilde{\mathbf{P}}_m^{(k)}) \left(\mathrm{sign}(\tilde{\mathbf{P}}_m^{(k)}) - \mathbf{1}\right), \\ &m = 1, 2, \cdots, M. \end{aligned} \tag{16}$$

Fig.1.b is the high frequency cases of $f_k \geq f_{Low}$, the maximum phase shift is $2\pi \lceil D f_k / c \rceil$. This means the alternative number of $P_{nm}^{(k)}$ becomes $L_k = \lceil D f_k / c \rceil$. In this case, we need to extend the phase search space from 2π to $2\pi L_k$, and the total number of possible $\mathbf{P}_m^{(k)}$ is $M L_k^{M-1}$.

3.3. Solution for Phase Uncertainty

Given the pruned possible phase shift vectors, we need to find the right one among them. Based on the the unit norm definition of $\mathbf{a}^{(k)}$, the right phase shift should satisfy

$$\left(\mathbf{P}_c^{(k)}\right)^T \mathbf{P}_c^{(k)} = \frac{4\pi^2 f_k^2 \kappa}{c^2}. \tag{17}$$

This norm constraints of $\mathbf{P}_c^{(k)}$ can be used as a criterion that tests the validation of all the possible phase shifts and finds the right one.

4. PERFORMANCE ANALYSIS

To evaluate a source localization method, criteria such as error covariance and CRB are used. In this section, the error covariance of our FDSL is provided and compared with the CRB of the AML approach.

Recall Eq. (10), the error of $\mathbf{r}_s$ can be approximated by

$$\Delta \mathbf{r}_s = \frac{\partial \mathbf{r}_s}{\partial \mathbf{a}^T} \Delta \mathbf{a}, \tag{18}$$

where $\frac{\partial \mathbf{r}_s}{\partial \mathbf{a}^T} = \left[\frac{\partial \mathbf{r}_s}{\partial \mathbf{a}_1^T}, \frac{\partial \mathbf{r}_s}{\partial \mathbf{a}_2^T}, \cdots, \frac{\partial \mathbf{r}_s}{\partial \mathbf{a}_H^T}\right]$, $\frac{\partial \mathbf{r}_s}{\partial \mathbf{a}_h^T} = \left[\frac{\partial \mathbf{r}_s}{\partial \mathbf{a}(1)}, \frac{\partial \mathbf{r}_s}{\partial \mathbf{a}(2)}\right]$, $\Delta \mathbf{a} = \left[\Delta \mathbf{a}_1^T, \Delta \mathbf{a}_2^T, \cdots, \Delta \mathbf{a}_H^T\right]^T$.

Assume the 1st sensor of the hth array has the smallest phase, the error of $\mathbf{P}_{hc}^{(k)}$ can be given by

$$\Delta \mathbf{P}_{hc}^{(k)} = \left(\mathbf{I} - \frac{\mathbf{1}}{M}\right) \begin{bmatrix} 0 & \mathbf{0}^T & 0 & \mathbf{0}^T \\ \mathbf{E}_1 & \mathbf{E}_2 & \mathbf{E}_3 & \mathbf{E}_4 \end{bmatrix} \begin{bmatrix} \Delta \mathrm{Re}(\mathbf{N}_h(k)) \\ \Delta \mathrm{Im}(\mathbf{N}_h(k)) \end{bmatrix}. \tag{19}$$

$$\begin{aligned} &\mathbf{E}_1 = [\varepsilon_{2,1}^1, \varepsilon_{3,1}^1, \cdots, \varepsilon_{M,1}^1]^T, && \mathbf{E}_2 = \mathrm{diag}(\varepsilon_{2,1}^2, \cdots, \varepsilon_{M,1}^M), \\ &\mathbf{E}_3 = [\upsilon_{2,1}^1, \upsilon_{3,1}^1, \cdots, \upsilon_{M,1}^1]^T, && \mathbf{E}_4 = \mathrm{diag}(\upsilon_{2,1}^2, \cdots, \upsilon_{M,1}^M), \\ &\varepsilon_{m,1}^1 = \frac{\mathrm{Im}(X_1(k))}{|X_1(k)|^2}, && \upsilon_{m,1}^1 = \frac{-\mathrm{Re}(X_1(k))}{|X_1(k)|^2}, \\ &\varepsilon_{m,1}^m = \frac{-\mathrm{Im}(X_m(k))}{|X_m(k)|^2}, && \upsilon_{m.1}^m = \frac{\mathrm{Re}(X_m(k))}{|X_m(k)|^2}. \end{aligned} \tag{20}$$

Here $\varepsilon_{m,1}^1$, $\upsilon_{m,1}^1$, $\varepsilon_{m,1}^m$ and $\upsilon_{m,1}^m$ are the partial derivatives of $P_{m1}^{(k)}$ to $\mathrm{Re}(X_1(k))$, $\mathrm{Im}(X_1(k))$, $\mathrm{Re}(X_m(k))$ and $\mathrm{Im}(X_m(k))$ respectively.

After some derivations, the covariance of $\Delta \mathbf{P}_{hc}^{(k)}$ and $\Delta \mathbf{a}_h^{(k)}$ are

$$\begin{aligned} &\mathrm{E}(\Delta \mathbf{P}_{ch}^{(k)} \Delta \left(\mathbf{P}_{ch}^{(k)}\right)^T) = \tfrac{\sigma^2}{2 S_{hk}^2} \left(\mathbf{I} + \mathbf{1}_{M\times M}\right), \\ &\mathrm{E}(\Delta \mathbf{a}_h^{(k)} \Delta \left(\mathbf{a}_h^{(k)}\right)^T) = \tfrac{N c^2 \sigma^2}{8 \kappa \pi^2} \tfrac{\mathbf{I}}{f_k^2 S_{hk}^2}. \end{aligned} \tag{21}$$

Observe that the error covariance of $\Delta \mathbf{a}_h^{(k)}$ is proportional to $1/f_k^2 S_{hk}^2$, frequency with larger $f_k^2 S_{hk}^2$ has small error covariance. If we assign $w_k = f_k^2 S_{hk}^2$ to each frequency when calculating the mean value of different $\mathbf{a}_h^{(k)}$, the weighted summation of $\mathbf{a}_h^{(k)}$ can be given by

$$\Delta\mathbf{a}_h = \sum_{k=1}^{K} w_k \Delta\mathbf{a}_h^{(k)} / \sum_{k=1}^{K} w_k. \tag{22}$$

Assume the noise $\mathbf{n}_h(k)$ at different frequency is independent, the error covariance of $\Delta\mathbf{a}_h$ is

$$\Delta\mathbf{a}_h\Delta\mathbf{a}_h^T = \left(\frac{Nc^2\sigma^2}{8\pi^2\kappa}\right)\frac{1}{\mu_h}, \tag{23}$$

where $\mu_h = \sum_{k=1}^{K} f_k^2 S_{hk}^2$. Recall Eq. (10), the partial derivation of $\mathbf{r}_s$ is given by

$$\begin{aligned}\frac{\partial\mathbf{r}_s}{\partial\mathbf{a}_h(1)} &= -\mathbf{U}^{-1}\frac{\partial\mathbf{U}}{\partial\mathbf{a}_h(1)}\mathbf{U}^{-1}\mathbf{V} + \mathbf{U}^{-1}\frac{\partial\mathbf{V}}{\partial\mathbf{a}_h(1)} \\ &= -\mathbf{U}^{-1}\mathbf{z}_{h1}\left(\Delta\mathbf{r}_h\right),\end{aligned} \tag{24}$$

in which $\mathbf{z}_{h1} = \mathbf{T}\left(\mathbf{a}_h\mathbf{e}_1{}^T + \mathbf{e}_1\mathbf{a}_h^T\right)\mathbf{T}^T$, $\mathbf{e}_1 = [1,0]^T$, $\Delta\mathbf{r}_h = (\mathbf{r}_s - \mathbf{r}_h)$. Combine Eqs. (18-23), the covariance of $\Delta\mathbf{r}_s$ is

$$\begin{aligned}\Delta\mathbf{r}_s\Delta\mathbf{r}_s^T &= -\mathbf{U}^{-1}\sum_{h=1}^{H}\frac{\partial\mathbf{r}_s}{\partial\mathbf{a}_h^T}\Delta\mathbf{a}_h\Delta\mathbf{a}_h^T\frac{\partial\mathbf{r}_s^T}{\partial\mathbf{a}_h^T}\mathbf{U}^{-1} \\ &= \frac{Nc^2\sigma^2}{8\kappa\pi^2}\mathbf{U}^{-1}\sum_{h=1}^{H}\frac{\boldsymbol{\alpha}_h}{\mu_h}\mathbf{U}^{-1},\end{aligned} \tag{25}$$

in which $\boldsymbol{\alpha}_h = \mathbf{z}_h\Delta\mathbf{r}_h\Delta\mathbf{r}_h^T\mathbf{z}_h^T$. After some simple calculations, the error covariance of $\mathbf{r}_s$ is

$$\mathrm{COV}(\mathbf{r}_s) = \frac{Nc^2\sigma^2}{8\kappa\pi^2}\mathbf{U}^{-1}\sum_{h=1}^{H}\frac{\mathbf{T}\Delta\mathbf{r}_h\Delta\mathbf{r}_h^T\mathbf{T}}{\mu_h}\mathbf{U}^{-1}. \tag{26}$$

For comparison, the CRB [9] of source localization is

$$\mathrm{CRB}(\mathbf{r_s}) = \frac{N\sigma^2c^2}{8\kappa\pi^2}\left(\mathbf{T}\sum_{k=1}^{K}f_k^2\sum_{h=1}^{H}S_{hk}^2\frac{\Delta\mathbf{r}_h\Delta\mathbf{r}_h^T}{|\Delta\mathbf{r}_h|^4}\mathbf{T}^T\right)^{-1}. \tag{27}$$

5. SIMULATION RESULTS

In this section, simulations are carried out to validate our FDSL approach. Four circular arrays with diameter 7.5cm are implemented at $[-120,-120]m$, $[-120,120]m$, $[120,-120]m$, $[120,120]m$, and a real bird call of Bewick's Wren (BEWR) is used as source signal in simulations.

Fig. 2 shows the comparison between the CRB of AML approach and the COV of the proposed FDSL approach. The SNR=10dB and 20 snapshots are used for each source localization estimation. The COV of the FDSL approach is 37% higher than the CRB of the AML approach on average, but it is still within an acceptable range.

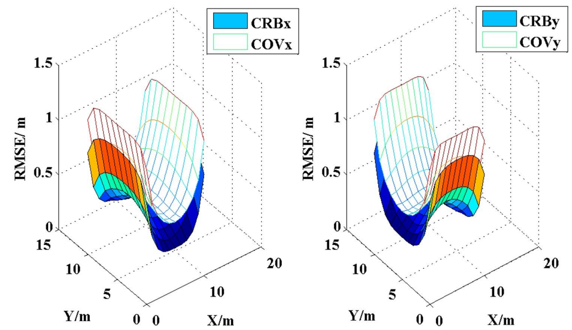

Fig. 2. Comparison between CRB and COV

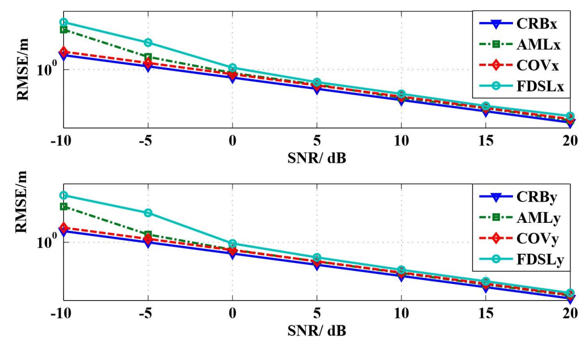

Fig. 3. Comparison among CRB, COV and the RMSEs of AML and FDSL

Further simulations are conducted to compare the CRB and COV values with the RMSEs of the AML and the FDSL approaches. Both methods approach their theoretical performance limits with increasing SNR. Although the FDSL has 37% performance degradation with respect to the AML, the processing time of the FDSL is only 3% of the AML approach. Consider both the computational complexity and accuracy, the FDSL approach shows its superiority compared to the AML approach.

6. CONCLUSION

In this paper, a novel FDSL estimation approach is proposed. The source localization problem is considered from an alternative perspective of phase calculation. Thus, traditional exhaustive search based AML approach can be replaced by a light weight linear search problem. Also the array geometry information is used to solve the phase uncertainty problem. Simulation using experiment data validates the feasibility of the FDSL approach and shows its superiority over the AML approach.

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