Robust Expectation-Maximization Algorithm for Multiple Wideband Acoustic Source Localization in the Presence of Nonuniform Noise Variances

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***Abstract*—Wideband source localization using acoustic sensor networks has been drawing a lot of research interest recently. The maximum-likelihood is the predominant objective which leads to a variety of source localization approaches. However, the robust and efficient optimization algorithms are still being pursuit by researchers since different aspects about the effectiveness of such algorithms have to be addressed on different circumstances. In this paper, we would like to combat the source localization based on the realistic assumption where the sources are corrupted by the noises with nonuniform variances. We focus on the two popular source localization methods for solving this problem, namely the SC-ML (stepwise-concentrated maximum-likelihood) and AC-ML (approximately-concentrated maximum likelihood) algorithms. We explore the respective limitations of these two methods and design a new expectation maximization (EM) algorithm. Furthermore, we provide the Cramer–Rao lower bound (CRLB) for all these three methods. Through Monte Carlo simulations, we demonstrate that our proposed EM algorithm outperforms the SC-ML and AC-ML methods in terms of the localization accuracy, and the root-mean-square (RMS) error of our EM algorithm is closer to the derived CRLB than both SC-ML and AC-ML methods.**

***Index Terms*—Cramer–Rao lower bound (CRLB), expectation maximization (EM) algorithm, source localization.**

I. Introduction

SOURCE localization using low-cost and low-complexity sensor arrays has been the active research area in the fields of radar, sonar, geophysics, wireless systems, and acoustic tracking for years [1], [2]. Recently, the wideband source localization in the near field has drawn a lot of research interest in the signal processing applications [3]–[6]. Extensive studies for the wideband source localization can be found in [3] and [4]. Among them, the maximum-likelihood (ML) approach in [3] has been regarded as the optimal and robust scheme for coherent source signals. However, when the multiple sources are present, the ML approach facilitates a nonlinear optimization problem, which is impractical especially for the energy-constrained sensor networks. In addition, many of the existing ML estimators are based on the unrealistic spatially white noise assumption across different sensors [5]–[7], where the noise process at each sensor is assumed to be spatially uncorrelated-white-Gaussian with an identical variance. It is shown that under this assumption, the ML estimates of the unknown parameters (source waveforms/spectra and noise variance) can be expressed as the respective functions of the source locations and the number of independent parameters to be estimated is greatly reduced. Thus, this assumption, although unrealistic, substantially reduces the search space and usually leads to more efficient localization algorithms. Hence, various wideband ML source location estimators were proposed in [3].

However, this spatially white noise (SWN) assumption is unrealistic in many applications. In several practical applications [7], the sensors are sparsely placed so that the sensor noise processes are spatially uncorrelated. However, the noise variance of each sensor can still be quite different due to either the variation of the manufacturing process, the imperfection of the sensor array calibration or the "unquiet" background. As a result, the spatial noise covariance matrix (across the sensors) can be modeled as a diagonal matrix where the diagonal elements in general are not identical. Note that this noise model is definitely not a special case of the ARMA model as was explained in [8]. Furthermore, the source location estimators derived from the SWN assumption would often not provide satisfactory results in the real environment since the algorithms derived from the SWN assumption blindly treat all sensors equally in the estimated likelihood. Motivated by the arguments above, in [7], two DOA calculation algorithms, namely *stepwise-concentrated maximum-likelihood estimator* (SC-ML) and *approximately-concentrated maximum likelihood algorithm* (AC-ML), have been recently proposed for the multiple wideband sources. Although both SC-ML and AC-ML methods can be extended for the source localization, the robustness issue still remain challenging in this research area. This is the primary reason why we would like to dedicate this paper to addressing these two issues by designing a new source localization scheme.

Felder and Weinstein proposed the generic expectation-maximization (EM) algorithm in [9] to estimate the parameters associated with the superimposed signals and employed it for the array signal processing in [10]. EM-based techniques have also been applied for the multisensor signal enhancement [11]–[13]. In addition, EM-based narrowband source localization algorithms were proposed by [14] and [15]. In this paper,

Manuscript received April 07, 2010; accepted May 04, 2010. Date of publication June 10, 2010; date of current version January 21, 2011. This work was supported in part by the Information Technology Research Award for National Priorities NSF-ECCS 0426644, Networking Technology and Systems Award NSF-CNS 0963793 from National Science Foundation, and DoD-DEPSCoR Grant N0014-08-1-0856 from Office of Naval Research. The associate editor coordinating the review of this paper and approving it for publication was Prof. Henry Leung.

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Digital Object Identifier 10.1109/JSEN.2010.2050311

we modify the EM algorithm to tackle with the general multiple source localization problem when the wideband sources are present in the near field, which evolves from the simple DOA estimation method for the narrowband sources in the far field in [16]. If the wideband sources are considered, the source signal signature or characteristics is unavailable at the sensor array and the method in [14]–[16] cannot be applied according to [17], [18]. Therefore, similar to [17], [18], we use the discrete-Fourier transform (DFT) filter bank to decompose the wideband signals collected by the sensors and then estimate the complete set of parameters involving source waveforms (or spectra) and source locations. Note that our previous works in [17], [18] can only deal with the source localization problem under the unrealistic SWN assumption. In this paper, we reformulate the source localization problem for the realistic SNWN assumption and design a new EM-based localization algorithm for multiple wideband sources and it can be shown that our proposed algorithm is much more computationally efficient and robust than the existing SC-ML and AC-ML methods (we have extended the original SC-ML and AC-ML methods in [7] which could only solve the DOA problem in [8] to combat the source localization problem).

The rest of this paper is organized as follows. The problem formulation and the signal model are introduced in Section II. The maximum-likelihood source-location estimators for both SWN and SNWN models are introduced in Section III. The novel EM algorithm for wideband source localization in the near field under the SNWN assumption is derived and discussed in Section IV. In addition, the Cramer–Rao lower bound (CRLB) derivation will be manifested in Section V. Monte Carlo simulation results for demonstrating our proposed new EM method and illustrating our newly derived robustness analysis will be provided in Section VI. Conclusion will be drawn in Section VII.

Nomenclatures: The sets of all real and complex numbers are denoted by $\mathcal{R}$ and $\mathcal{C}$, respectively. A vector is denoted by $\underline{A}$ and a matrix is denoted by $\widetilde{A}$. The statistical expectation operation is expressed as $\mathbb{E}\{\}$. Besides, $\widetilde{A}^T$, $\widetilde{A}^*$, $\widetilde{A}^H$, $\det(\widetilde{A})$, $\widetilde{A}^\dagger$, and $\operatorname{trace}(\widetilde{A})$ stand for the transpose, conjugate, Hermitian adjoint, determinant, pseudo-inverse, and trace of the matrix $\widetilde{A}$, respectively. In addition, $\odot$ stands for the Hadamard matrix product operator, and $\|\|$ stands for the Euclidean norm.

II. Signal Model

According to [3], we consider a randomly distributed array of P sensors to collect the data from M sources. Since the sources are assumed to be in the near field, the signal gains are different across the sensors. Thus, the signal collected by the pth sensor at a discrete time instant n is given by

$$x_p(n) = \sum_{m=1}^{M} a_p^{(m)} s^{(m)}\left(n - t_p^{(m)}\right) + w_p(n) \tag{1}$$

for $n = 0, 1, \ldots, L-1$, $p = 1, \ldots, P$, $m = 1, \ldots, M$, where $a_p^{(m)}$ is the gain of the mth source signal arriving at the pth sensor; $s^{(m)}(n)$ denotes the mth source signal waveform; $t_p^{(m)}$ is the propagation delay (in data samples) incurred from the mth source to the pth sensor; $w_p(n)$ represents the zero-mean independently identically distributed (i.i.d.) noise process. Several crucial parameters are specified as follows: $t_p^{(m)} \stackrel{\text{def}}{=} F_s(\|\underline{r_s}^{(m)} - \underline{r_p}\|)/(v)$: the propagation delay from the mth source to the pth sensor:

$\underline{r_s}^{(m)} \in \mathcal{R}^{2\times 1}$: the mth source location,

$\underline{r_p} \in \mathcal{R}^{2\times 1}$: the p^{th} sensor location,

v: the source signal propagation speed in meters/second,

F_s: sampling frequency.

Taking the N-point DFT of both sides in (1) and reserving a half of them due to the symmetry property, we have

$$\underline{X}(k) = \widetilde{D}(k)\underline{S}(k) + \underline{U}(k), \text{for } k = 0, 1, \ldots, \frac{N}{2} - 1 \tag{2}$$

where

$$\underline{X}(k) \stackrel{\text{def}}{=} [X_1(k), \ldots, X_P(k)]^T \in \mathcal{C}^{P\times 1} \tag{3}$$

and $X_p(k)$ is the kth DFT point of $x_p(n)$, $p = 1, \ldots, P$. The symbols for the right-hand side of (2) are clarified as follows:

$$\widetilde{D}(k) \stackrel{\text{def}}{=} [\underline{d}^{(1)}(k), \ldots, \underline{d}^{(M)}(k)] \in \mathcal{C}^{P\times M} \tag{4}$$

consists of M *steering vectors*, each given by

$$\underline{d}^{(m)}(k) \stackrel{\text{def}}{=} \left[d_1^{(m)}(k), \ldots, d_P^{(m)}(k)\right]^T \in \mathcal{C}^{P\times 1}, m = 1, \ldots, M \tag{5}$$

where

$$d_p^{(m)}(k) \stackrel{\text{def}}{=} a_p^{(m)} e^{-\frac{j2\pi k t_p^{(m)}}{N}} \tag{6}$$

and $j \stackrel{\text{def}}{=} \sqrt{-1}$. Note that

$$\underline{S}(k) \stackrel{\text{def}}{=} \left[S^{(1)}(k), \ldots, S^{(M)}(k)\right]^T \in \mathcal{C}^{M\times 1} \tag{7}$$

consists of M individual source signal spectra, each given by $S^{(m)}(k)$ where $S^{(m)}(k)$ is the kth DFT point of $s^{(m)}(n)$, $m = 1, \ldots, M$.

In reality, the source signal spectral vector $\underline{S}(k)$ is unknown and deterministic. The noise spectral vector $\underline{U}(k) \in \mathcal{C}^{P\times 1}$ is a complex-valued zero-mean spatially uncorrelated Gaussian process with the following covariance matrix:

$$\widetilde{Q} \stackrel{\text{def}}{=} \mathbb{E}\left\{\underline{U}(k)\underline{U}(k)^H\right\} = \begin{bmatrix} q_1 & 0 & \cdots & 0 \\ 0 & q_2 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & q_P \end{bmatrix} \in \mathcal{C}^{P\times P}, \quad \forall k. \tag{8}$$

In general, q_p, $p = 1, 2, \ldots, P$, are not necessarily identical to each other under the SNWN assumption. Hence, we need to deal with the realistic source localization problem in the presence of the nonuniform noise variances thereupon.

III. Maximum-Likelihood for Source Localization

Prior to the establishment of the log-likelihood for the source localization in the presence of the nonuniform noise variances as stated by (8), we start from the conventional maximum-likelihood formulation for the identical noise variance across the sensors.

A. Conventional Maximum-Likelihood for Source Localization in the Presence of Identical Noise Variance (SWN)

According to the signal model given by (2) together with the noise variance constraint as $\widetilde{Q} = \sigma^2 \widetilde{I}$, where σ^2 is the noise variance and $\widetilde{I}$ is a $P \times P$ identity matrix, the maximum-likelihood source localization formulation can be facilitated as [1], [3], [7]. We highlight the relevant pivotal formulae here.

Let $\underline{r_s}$, $\widetilde{S}$, σ^2 represent all the unknown parameters in (2) necessary to be estimated, where

$$\underline{r_s} \stackrel{\text{def}}{=} \left[\underline{r_s}^{(1)^T}, \ldots, \underline{r_s}^{(m)^T}, \ldots, \underline{r_s}^{(M)^T}\right]^T \in \mathcal{R}^{2M\times 1} \quad (9)$$

and

$$\widetilde{S} \stackrel{\text{def}}{=} [\underline{S}(0)^T, \ldots, \underline{S}(N/2-1)^T]^T \in \mathcal{C}^{(\frac{NM}{2})\times 1}. \quad (10)$$

In addition, we denote the *residual vector* as

$$\underline{g}(k) \stackrel{\text{def}}{=} [g_1(k), \ldots, g_P(k)]^T = \underline{X}(k) - \widetilde{D}(k)\underline{S}(k) \in \mathcal{C}^{P\times 1}. \quad (11)$$

Thus, the likelihood function is given by

$$f(\underline{r_s}, \widetilde{S}, \sigma^2) \stackrel{\text{def}}{=} \frac{1}{\pi^{PN/2}\sigma^{PN}} \exp\left\{-\frac{1}{\sigma^2}\sum_{k=0}^{N/2-1}\left\|\underline{g}(k)\right\|^2\right\}. \quad (12)$$

Taking the logarithm of (12) and neglecting all the constant terms, we can derive the log-likelihood function $L(\underline{r_s}, \widetilde{S}, \sigma^2)$ as follows:

$$L(\underline{r_s}, \widetilde{S}, \sigma^2) = -\frac{PN}{2}\log\left(\sigma^2\right) - \frac{1}{\sigma^2}\sum_{k=0}^{N/2-1}\|\underline{g}(k)\|^2 \quad (13)$$

and the corresponding maximum-likelihood estimates are

$$\begin{aligned}(\widehat{\underline{r_s}}, \widehat{\widetilde{S}}, \widehat{\sigma^2}) &= \arg\max_{(\underline{r_s}, \widetilde{S}, \sigma^2)}\{L(\underline{r_s}, \widetilde{S}, \sigma^2)\} \\ &= \arg\min_{(\underline{r_s}, \widetilde{S}, \sigma^2)}\left(\sum_{k=0}^{N/2-1}\left\|\underline{g}(k)\right\|^2\right) \\ &= \arg\min_{(\underline{r_s}, \widetilde{S}, \sigma^2)}\left(\sum_{k=0}^{N/2-1}[\underline{X}(k) - \widetilde{D}(k)\underline{S}(k)]^H\right. \\ &\qquad \left.\times[\underline{X}(k) - \widetilde{D}(k)\underline{S}(k)]\right). \end{aligned} \quad (14)$$

Thus, according to (14), we can write

$$\widehat{\underline{S}}(k) = \widetilde{D}(k)^{\dagger}\underline{X}(k) = (\widetilde{D}(k)^H\widetilde{D}(k))^{-1}\widetilde{D}(k)^H\underline{X}(k) \quad (15)$$

and

$$\widehat{\underline{r_s}} = \arg\min_{\underline{r_s}}\sum_{k=0}^{N/2-1}\|\underline{X}(k) - \widetilde{D}(k)^{\dagger}\underline{X}(k)\|^2. \quad (16)$$

B. Maximum-Likelihood for Source Localization in the Presence of Nonuniform Noise Variances (SNWN)

In this subsection, we will introduce the nonuniform maximum-likelihood source localization formulation according to the recent literature [7], [8] for a more realistic SNWN model. Let $\underline{r_s}$, $\widetilde{S}$, $\underline{q}$ be the parameters to be estimated for this case, where $\underline{q} \stackrel{\text{def}}{=} [q_1, \ldots, q_P]^T \in \mathcal{R}^{P\times 1}$ is the vector consisting of the diagonal elements in $\widetilde{Q}$ given by (8). The likelihood function of $(\underline{r_s}, \widetilde{S}, \underline{q})$ can be expressed as

$$f(\underline{r_s}, \widetilde{S}, \underline{q}) \stackrel{\text{def}}{=} \frac{1}{(\pi^p\det(\widetilde{Q}))^{N/2}} \times \exp\left\{-\sum_{k=0}^{N/2-1}\underline{g}(k)^H\widetilde{Q}^{-1}\underline{g}(k)\right\}. \quad (17)$$

Then, we have the following log-likelihood function $L(\underline{r_s}, \widetilde{S}, \underline{q})$ by taking the logarithm of (17) and neglecting all the constant terms

$$L(\underline{r_s}, \widetilde{S}, \underline{q}) = -\frac{N}{2}\sum_{p=1}^{P}\log\left(q_p\right) - \sum_{k=0}^{N/2-1}\|\underline{\dot{g}}(k)\|^2 \quad (18)$$

where

$$\underline{\dot{g}}(k) \stackrel{\text{def}}{=} \widetilde{Q}^{-1/2}\underline{g}(k) = \underline{\dot{X}}(k) - \dot{\widetilde{D}}(k)\underline{S}(k) \quad (19)$$

$$\underline{\dot{X}}(k) \stackrel{\text{def}}{=} \widetilde{Q}^{-1/2}\underline{X}(k) \quad (20)$$

$$\dot{\widetilde{D}}(k) \stackrel{\text{def}}{=} \widetilde{Q}^{-1/2}\widetilde{D}(k). \quad (21)$$

Consequently, we may obtain the maximum-likelihood estimates for $(\underline{r_s}, \widetilde{S}, \underline{q})$ as

$$(\widehat{\underline{r_s}}, \widehat{\widetilde{S}}, \widehat{\underline{q}}) = \arg\max_{(\underline{r_s}, \widetilde{S}, \underline{q})} L(\underline{r_s}, \widetilde{S}, \underline{q}). \quad (22)$$

Similar to the derivation in Section III-A, we can obtain the estimate of the pth element in $\underline{q}$ as

$$\widehat{q}_p = \frac{2}{N}\sum_{k=0}^{N/2-1}|g_p(k)|^2 = \frac{2}{N}\|\underline{g_p}\|^2 \quad (23)$$

where $g_p(k)$ denotes the pth element of the residual vector $\underline{g}(k)$ and

$$\underline{g_p} \stackrel{\text{def}}{=} \left[g_p(0), \ldots, g_p\left(\frac{N}{2}-1\right)\right]^T \in \mathcal{C}^{N/2\times 1}. \quad (24)$$

Substituting (24), (23) into (18), we can convert the log-likelihood function to a new version in terms of $\underline{r_s}$ and $\widetilde{S}$ and then get the ML estimators for $\underline{r_s}$ and $\widetilde{S}$ given by

$$(\widehat{\underline{r_s}}, \widehat{\widetilde{S}}) = \arg\max_{(\underline{r_s}, \widetilde{S})}\left(-\sum_{p=1}^{P}\log\|\underline{g_p}\|^2\right) \quad (25)$$

and

$$\widehat{\underline{S}}(k) = \dot{\widetilde{D}}(k)^{\dagger}\underline{\dot{X}}(k). \quad (26)$$

Substituting (26) into (25), we can obtain the maximum-likelihood estimates of $\underline{r_s}$ as

$$(\widehat{\underline{r_s}}) = \arg\max_{(\underline{r_s})}\left(-\sum_{p=1}^{P}\log\|\underline{g_p}\|^2\right) \tag{27}$$

where $\underline{g_p}$ is defined by (24), and

$$\underline{g}(k) = \underline{X}(k) - \widetilde{D}(k)\tilde{\dot{D}}(k)^{\dagger}\tilde{\dot{X}}(k). \tag{28}$$

IV. EM Wideband Source-Localization Algorithm for Distinct Noise Variances

A. Individual Likelihood Formulation for Source Localization

The EM algorithm is a well-known iterative algorithm for the maximum-likelihood estimation. The complicated nonlinear optimization problem in (22) and (27) can be simplified using the EM procedure incorporated with the *augmented (complete) data* corresponding to the individual incident source signals. First, we denote the received signal spectrum as $X_p^{(m)}(k), 1 \le p \le P, 1 \le m \le M, 0 \le k \le N-1$ from the mth source to the pth sensor. Then, we define the augmented data as $\{\underline{X}^{(m)}(k); 1 \le m \le M, 0 \le k \le N-1\}$, where $\underline{X}^{(m)}(k) \stackrel{\text{def}}{=} [X_1^{(m)}(k), \ldots, X_P^{(m)}(k)]^T \in \mathcal{C}^{P\times 1}$.

In addition, the relationship between the observed (incomplete) data $\underline{X}(k)$ and the unobserved latent (complete) data is established as

$$\underline{X}(k) = \sum_{m=1}^{M}\underline{X}^{(m)}(k). \tag{29}$$

According to (2), (5), (7), and (29), for a single source signal (the mth source), we have

$$\underline{X}^{(m)}(k) \stackrel{\text{def}}{=} \underline{d}^{(m)}(k)S^{(m)}(k) + \underline{U}^{(m)}(k), \quad \text{for } k = 0, 1, \ldots, N/2-1 \tag{30}$$

where $\underline{U}^{(m)}(k) \in \mathcal{C}^{P\times 1}$ is the complex-valued zero-mean uncorrelated Gaussian noise in the sole presence of the mth source.

According to (22), (27), and (30), we have

$$\left(\widehat{\underline{r_s}}^{(m)}, \widehat{\underline{S}}^{(m)}, \widehat{\underline{q}}^{(m)}\right) = \arg\max_{(\underline{r_s}^{(m)}, \underline{S}^{(m)}, \underline{q}^{(m)})} L\left(\underline{r_s}^{(m)}, \underline{S}^{(m)}, \underline{q}^{(m)}\right), 1 \le m \le M \tag{31}$$

where $\underline{S}^{(m)} \stackrel{\text{def}}{=} [S^{(m)}(0)\cdots S^{(m)}(N/2-1)]^T \in \mathcal{C}^{N/2\times 1}$ and $\underline{q}^{(m)} \stackrel{\text{def}}{=} [q_1^{(m)}, \ldots, q_P^{(m)}]^T \in \mathcal{C}^{P\times 1}$ is the vector consisting of the diagonal elements in $\widetilde{Q}^{(m)} \stackrel{\text{def}}{=} \mathbb{E}\{\underline{U}^{(m)}(k)(\underline{U}^{(m)}(k))^H\} \in \mathcal{C}^{P\times P}, \forall k$. Let

$$\underline{\dot{d}}^{(m)}(k) \stackrel{\text{def}}{=} \left(\widetilde{Q}^{(m)}\right)^{-1/2}\underline{d}^{(m)}(k), \tag{32}$$

and

$$\underline{\dot{X}}^{(m)}(k) \stackrel{\text{def}}{=} \left(\widetilde{Q}^{(m)}\right)^{-1/2}\underline{X}^{(m)}(k). \tag{33}$$

According to (24), we denote the pth element of the particular residual vector $\underline{g}^{(m)}(k)$ as $g_p^{(m)}(k)$ when only source m is present, where

$$\underline{g}^{(m)}(k) = \underline{X}^{(m)}(k) - \underline{\dot{d}}^{(m)}(k)\underline{\dot{d}}^{(m)}(k)^{\dagger}\underline{\dot{X}}^{(m)}(k). \tag{34}$$

Similar to the derivation in Section III-B, (31) yields

$$\widehat{q}_p^{(m)} = \frac{2}{N}\sum_{k=0}^{N/2-1}\left|\left[g_p^{(m)}(k)\right]\right|^2 = \frac{2}{N}\left\|\underline{g_p}^{(m)}\right\|^2 \tag{35}$$

where

$$\underline{g_p}^{(m)} \stackrel{\text{def}}{=} \left[g_p^{(m)}(0), \ldots, g_p^{(m)}(N/2-1)\right]^T \in \mathcal{C}^{N/2\times 1}. \tag{36}$$

Consequently, the maximum-likelihood estimates $\widehat{\underline{r_s}}^{(m)}$,is given by

$$\left(\widehat{\underline{r_s}}^{(m)}\right) = \arg\max_{(\underline{r_s}^{(m)})}\left(-\sum_{p=1}^{P}\log\left(\|\underline{g_p}^{(m)}\|^2\right)\right). \tag{37}$$

According to (37), the source localization problem can be formulated as the independent maximization subproblems with respect to the individual likelihood functions.

B. New Expectation-Maximization (EM) Algorithm for Source Localization

In contrast to other existing algorithms for the source localization using the sensor signals in the presence of noises with identical variance [1], [3], [17], [18], we present a new EM algorithm here to solve the realistic source localization problem for sensor signals in the presence of noises with different variances, which has been tackled by [7] recently. Nevertheless, our proposed EM algorithm can be demonstrated to be more robust than the method proposed by [7].

The details of our proposed EM algorithm are introduced as follows (since our proposed algorithm can be decoupled across different sources in each iteration, we only need to address the steps for the source m and it can be run for other sources as well in parallel).

Initialization: Randomly initialize $[\widehat{\underline{r_s}}^{(m)}]^{[0]}$. Set the initial values for the entries in $[\widehat{\underline{q}}^{(m)}]^{[0]}$ and $[\widehat{\underline{q}}]^{[0]}$ as

$$\left[\widehat{\underline{q}}^{(m)}\right]^{[0]} = \frac{1}{M}\times[11\cdots 1]^T \in \mathcal{R}^{P\times 1} \tag{38}$$

and

$$[\widehat{\underline{q}}]^{[0]} = [11\cdots 1]^T \in \mathcal{R}^{P\times 1} \tag{39}$$

respectively.

Input (Given) Parameters at Iteration i: $[\widehat{\underline{q}}^{(m)}]^{[i-1]}$, $[\widehat{\underline{r_s}}^{(m)}]^{[i-1]}$.

Output Variables at Iteration i: $[\widehat{\underline{q}}^{(m)}]^{[i]}$, $[\widehat{\underline{r_s}}^{(m)}]^{[i]}$.

Given the input parameters, the EM algorithm for the ith iteration is stated next.

Expectation Step (E-Step): Calculate

$$\widehat{\widetilde{Q}}^{(m)} = \operatorname{diag}\left\{\left[\widehat{\underline{q}}^{(m)}\right]^{[i-1]}\right\} \tag{40}$$

where $\text{diag}\{\}$ converts the vector inside the associated braces into a diagonal matrix containing the vector's entries as the diagonal elements in the same order. Compute

$$\widetilde{Q} = \sum_{m=1}^{M} \widehat{\widetilde{Q}}^{(m)} \tag{41}$$

and

$$\alpha = \frac{\left[\text{trace}\left(\widehat{\widetilde{Q}}^{(m)}\right)\right]^2}{\left[\text{trace}\left(\widehat{\widetilde{Q}}\right)\right]^2}. \tag{42}$$

Calculate

$$t_p^{(m)} = F_s \frac{\left\| \left[\underline{\widehat{r}_s}^{(m)}\right]^{[i-1]} - \underline{r_p} \right\|}{v}. \tag{43}$$

According to (43), (6), (5), (4), and $a_p^{(m)} = 1, \forall p$ based on [7], determine $\underline{d}^{(m)}(k)$ and $\widetilde{D}(k)$. Next, follow (20), (21), and (26) to determine $\underline{\widehat{S}}(k)$ and $\widehat{S}^{(m)}(k)$, $k = 0, 1, \ldots, N/2 - 1$, where $\widehat{S}^{(m)}(k)$ is the mth element of $\underline{\widehat{S}}(k)$. Then, determine

$$\begin{aligned}\underline{\widehat{X}}^{(m)}(k) &= \mathbb{E}\left\{\underline{\widehat{X}}^{(m)}(k) | \underline{X}(k)\right\} \\ &= \underline{d}^{(m)}(k)\widehat{S}^{(m)}(k) + \alpha(\underline{X}(k) - \widetilde{D}(k)\underline{\widehat{S}}(k)), \\ &\qquad k = 0, 1, \ldots, N/2 - 1. \end{aligned} \tag{44}$$

Maximization Step (M-Step): Now, let

$$t_p^{(m)} = F_s \frac{\left\| \underline{r_s}^{(m)} - \underline{r_p} \right\|}{v} \tag{45}$$

where $\underline{r_s}^{(m)}$ is the variable coordinate and it has to be estimated in this step. Then, follow (45), (6), and (5) to facilitate $\underline{d}^{(m)}(k)$, $k = 0, 1, \ldots, N/2 - 1$, which involves the variable coordinate $\underline{r_s}^{(m)}$. Then, according to $\underline{d}^{(m)}(k)$, construct the following parameters:

$$\underline{\dot{d}}^{(m)}(k) = \left(\widehat{\widetilde{Q}}^{(m)}\right)^{(-1/2)} \underline{d}^{(m)}(k), k = 0, 1, \ldots, N/2 - 1 \tag{46}$$

which also involves the variable coordinate $\underline{r_s}^{(m)}$. According to the result from (44), calculate

$$\underline{\dot{\widehat{X}}}^{(m)}(k) = \left(\widehat{\widetilde{Q}}^{(m)}\right)^{(-1/2)} \underline{\widehat{X}}^{(m)}(k), k = 0, 1, \ldots, N/2 - 1. \tag{47}$$

Then, construct

$$\begin{aligned}\underline{\widehat{g}}^{(m)}(k) &= \underline{\dot{\widehat{X}}}^{(m)}(k) - \underline{\dot{d}}^{(m)}(k)\underline{\dot{d}}^{(m)}(k)^{\dagger}\underline{\dot{\widehat{X}}}^{(m)}(k), \\ &\qquad k = 0, 1, \ldots, N/2 - 1 \end{aligned} \tag{48}$$

which involves the variable coordinate $\underline{r_s}^{(m)}$ as well. Denote the pth element of $\underline{\widehat{g}}^{(m)}(k)$ as $\widehat{g}_p^{(m)}(k)$. Facilitate

$$\underline{\widehat{g}_p}^{(m)} = \left[\widehat{g}_p^{(m)}(0), \ldots, \widehat{g}_p^{(m)}(N/2 - 1)\right]^T \tag{49}$$

which involves the variable coordinate $\underline{r_s}^{(m)} \in \mathcal{R}^{2\times 1}$. Carry out

$$\left[\underline{\widehat{r}_s}^{(m)}\right]^{[i]} = \arg \min_{\underline{r_s}^{(m)}} \sum_{p=1}^{P} \log\left(\|\underline{\widehat{g}_p}^{(m)}\|^2\right). \tag{50}$$

Besides, calculate $t_p^{(m)} = F_s \frac{\left\|[\underline{\widehat{r}_s}^{(m)}]^{[i]} - \underline{r_p}\right\|}{v}$. Let $a_p^{(m)} = 1, \forall p$. Enumerate the parameters given by (44), (6), (5), (32), (47), (48), and (49) in this sequential order. Then, calculate

$$\left[\widehat{q_p}^{(m)}\right]^{[i]} = \frac{2}{N}\left\|\underline{\widehat{g}_p}^{(m)}\right\|^2, \quad p = 1, 2, \ldots, P. \tag{51}$$

Thus, obtain

$$\left[\underline{\widehat{q}}^{(m)}\right]^{[i]} = \left[\left[\widehat{q_1}^{(m)}\right]^{[i]}, \ldots, \left[\widehat{q_P}^{(m)}\right]^{[i]}\right]^T \in \mathcal{R}^{P\times 1}. \tag{52}$$

The above algorithm facilitates a recursive solution to multiple wideband source localization.

V. Robustness Analysis for Source Localization Algorithms

CRLB is often used to characterize the robustness of the estimation methods. In this section, by extending the CRLB presented in [7] for the simple DOA estimation problem, we derive the CRLB for the source localization problem to benchmark our EM method and the SC-ML/AC-ML schemes as

$$\frac{1}{\text{CRLB}} = 2\Re\left\{\sum_{k=0}^{N/2-1}\left\{\left[\dot{\widetilde{G}}(k)^H \widetilde{P}^{\perp}_{\dot{\widetilde{D}}(k)} \dot{\widetilde{G}}(k)\right] \odot \widetilde{R_s}(k)^T\right\}\right\} \tag{53}$$

where

$$\dot{\widetilde{G}}(k) \stackrel{\text{def}}{=} \widetilde{Q}^{-1/2}\widetilde{G}(k) \tag{54}$$

$$\widetilde{G}(k) \stackrel{\text{def}}{=} \left[\frac{\partial}{\partial \underline{r_s}^{(1)}}\underline{d}^{(1)}(k), \ldots, \frac{\partial}{\partial \underline{r_s}^{(M)}}\underline{d}^{(M)}(k)\right] \tag{55}$$

$$\widetilde{P}^{\perp}_{\dot{\widetilde{D}}(k)} \stackrel{\text{def}}{=} \widetilde{I} - \dot{\widetilde{D}}(k)\dot{\widetilde{D}}(k)^{\dagger} \tag{56}$$

$$\widetilde{R_s}(k) \stackrel{\text{def}}{=} \underline{S}(k)\underline{S}(k)^H. \tag{57}$$

Note that $\widetilde{Q}$, $\underline{d}^{(m)}(k)$, $\dot{\widetilde{D}}(k)$, and $\underline{S}(k)$ are given by (8), (5), (21), and (4), (7). We can rewrite (55) as

$$\widetilde{G}(k) = \frac{\partial \widetilde{D}(k)}{\partial \underline{r_s}^T} = -jF_s k\frac{2\pi}{Nv} \times \widetilde{F} \tag{58}$$

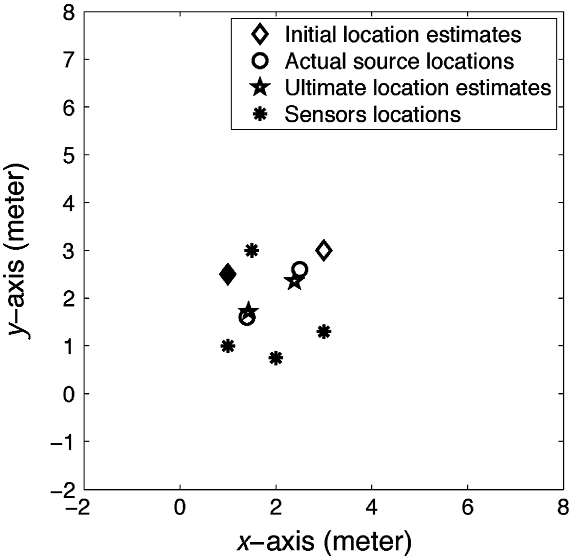

Fig. 1. The localization of two wideband (acoustic) sources in the near field corrupted by the noises with nonuniform variances (SNR is 10 dB). The initial location estimates and the ultimate location estimates resulted from the EM algorithm (three iterations are taken) are also demonstrated.

where (59) and (60) are shown at the bottom of the page. Note that $\underline{r_s}^{(m)} \stackrel{\text{def}}{=} [\chi_s^{(m)}, y_s^{(m)}]^T$ and $\underline{r_p} \stackrel{\text{def}}{=} [\chi_p, y_p]^T$.

VI. Simulation

The comparison is made among our newly proposed EM-based multiple wideband source localization scheme, the SC-ML method and the AC-ML method here. The sampling frequency is 100 kHz. The propagation speed is 345 meters/s. The data is simulated for a circularly-shaped array of five sensors using the recorded acoustic data acquired from [1] as shown in Fig. 1 (squares denote the sensor locations and circles denote the actual source locations). The sample size is $L = 200$ and the DFT size is $N = 256$. Throughout the simulation, the minimization in our EM method characterized by (50) is performed by Nelder–Mead direct search [3], while the optimization steps in both SC-ML and AC-ML methods are performed using the AM algorithm, which would lead to better performance than Nelder–Mead direct search in these two schemes [3], [7]. Moreover, the additive noises in all experiments are randomly generated by a Gaussian process using the computer and the signal-to-noise ratio (SNR) is defined according to [7] and [8].

A. A Localization Layout Example

Then we investigate the performance of the EM algorithm for estimating the two source locations in the presence of sensor noises with nonuniform variances, and compare with the SC-ML and AC-ML algorithms. The noise processes across different sensors have the covariance matrix as $\widetilde{Q} = \sigma^2 \text{diag}\,\{2, 3, 1, 5, 9\}$. One hundred Monte Carlo experiments are carried out using our EM method with randomly initialized source locations for a particular signal-to-noise ratio ($\text{SNR} = 10$ dB). The localization result from a certain experiment is depicted in Fig. 1, where the ultimate locations are achieved after three iterations of EM algorithm. We default the number of EM iterations as three in all Monte Carlo experiments.

B. Root-Mean-Square (RMS) Errors and Computational Complexities for Source Localization

For each SNR value ranging from 0 to 40 dB, we fix the initial source location estimates as depicted in Fig. 1 and carry out a hundred Monte Carlo experiments to obtain the average localization accuracy in terms of the root-mean-square (RMS) error in meters. The three corresponding RMS error curves to the three aforementioned schemes are depicted in Fig. 2. Then, we vary the initial location estimates around the circular areas with a one-meter diameter with respect to the two initial source-location estimates depicted in Fig. 1 and redo 100 Monte Carlo experiments similar to the setup generating Fig. 2. The results are depicted in Fig. 3. It is obvious that the accuracies of all three methods degrade from Figs. 2–3 since the initial conditions change. To further study this effect, we spread the initial location estimates over a broader area as depicted in Fig. 4 and redo 100 Monte Carlo experiments similar to Fig. 3. The average RMS error curves are demonstrated in Fig. 5. Next, we would like to investigate the performances of the three aforementioned

$$\widetilde{d} \stackrel{\text{def}}{=} \begin{Bmatrix} a_1^{(1)} e^{-\frac{j2\pi k t_1^{(1)}}{N}} \underline{\lambda_1}^{(1)} & a_1^{(2)} e^{-\frac{j2\pi k t_1^{(2)}}{N}} \underline{\lambda_1}^{(2)} & \dots & \dots & a_1^{(M)} e^{-\frac{j2\pi k t_1^{(M)}}{N}} \underline{\lambda_1}^{(M)} \\ \vdots & \vdots & \ddots & \dots & \vdots \\ a_P^{(1)} e^{-\frac{j2\pi k t_P^{(1)}}{N}} \underline{\lambda_P}^{(1)} & a_P^{(2)} e^{-\frac{j2\pi k t_P^{(2)}}{N}} \underline{\lambda_P}^{(2)} & \dots & \dots & a_P^{(M)} e^{-\frac{j2\pi k t_P^{(M)}}{N}} \underline{\lambda_P}^{(M)} \end{Bmatrix} \tag{59}$$

$$\begin{aligned} \underline{\lambda_p}^{(m)} &\stackrel{\text{def}}{=} \left[\frac{\partial d_p^{(m)}}{\partial \chi_s^{(m)}}, \frac{\partial d_p^{(m)}}{\partial y_s^{(m)}}\right] = \frac{\underline{r_s}^{(m)^T} - \underline{r_p}^T}{\|\underline{r_s}^{(m)} - \underline{r_p}\|} \in \mathcal{R}^{1\times 2}, \\ \frac{\partial d_p^{(m)}}{\partial \chi_s^{(m)}} &= \frac{\chi_s^{(m)} - \chi_p}{\sqrt{\left(\chi_s^{(m)} - \chi_p\right)^2 + \left(y_s^{(m)} - y_p\right)^2}}, \\ \frac{\partial d_p^{(m)}}{\partial y_s^{(m)}} &= \frac{y_s^{(m)} - y_p}{\sqrt{\left(\chi_s^{(m)} - \chi_p\right)^2 + \left(y_s^{(m)} - y_p\right)^2}}. \end{aligned} \tag{60}$$

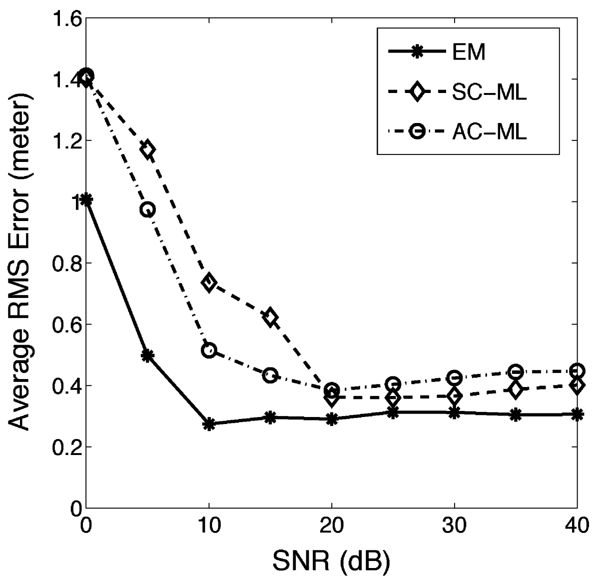

Fig. 2. Average RMS localization errors versus SNR for the sources corrupted by the noises with nonuniform variances. The initial location estimates are plotted in Fig. 1.

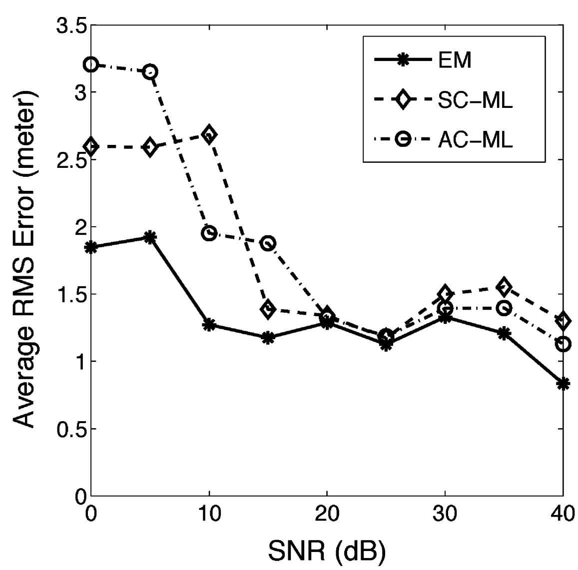

Fig. 3. Average RMS localization errors versus SNR for the sources corrupted by the noises with nonuniform variances. The initial source location estimates here are randomly chosen within the areas which are one meter around the initial location estimates used in Fig. 1.

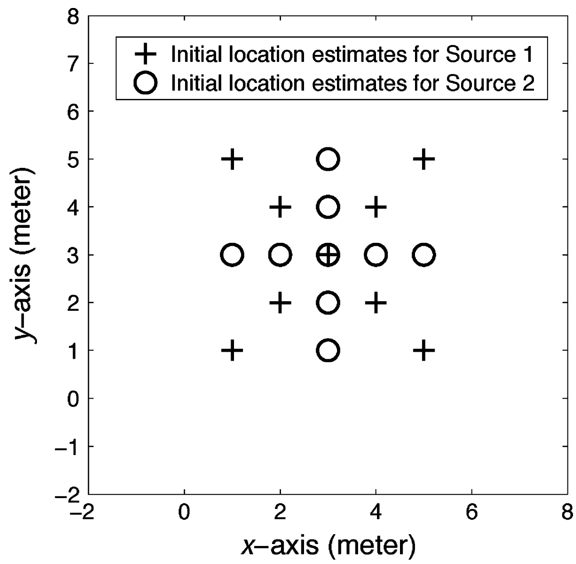

Fig. 4. The 18 different initial source location estimates.

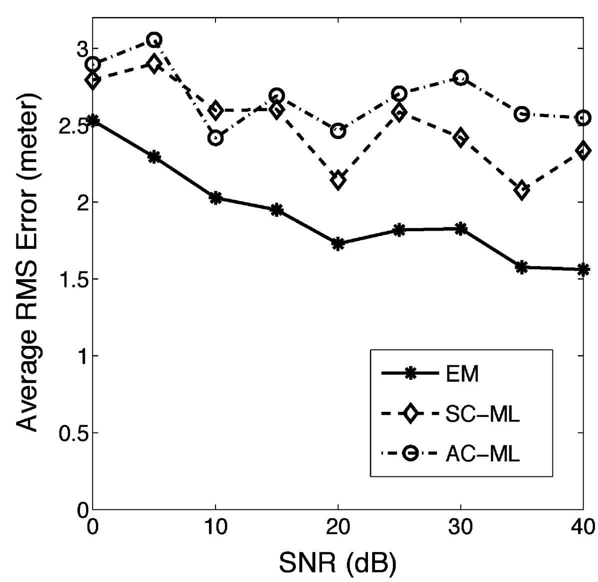

Fig. 5. Average RMS localization errors versus SNR for the sources corrupted by the noises with nonuniform variances. The initial source location estimates are plotted in Fig. 4.

localization methods for the sensor noises with identical variances (SWN). Thus, we choose the sensor noise covariance matrix as $\widetilde{Q} = \sigma^2 \mathrm{diag}\{1,1,1,1,1\}$ now. With this new noise covariance matrix, we redo the Monte Carlo experiments similar to those generating Figs. 2, 3, and 5. The corresponding results are plotted in Figs. 6–8, respectively. According to these two sets of experiments, our proposed EM algorithm greatly outperforms both SC-ML and AC-ML methods in all conditions. In addition, the accuracies of all three methods degrade due to the changes in the initial conditions for the SWN scenario as well. Besides, the performances of all these three schemes for the SWN case are not much different from those for the SNWN case, since the SWN model is a particular case of the SNWN model.

C. Robustness Analysis of Source Localization

We fix the initial source location estimates as those generating Fig. 1 and carry out a hundred Monte Carlo experiments again. The corresponding CRLBs for our EM method, the SC-ML (or AC-ML) method are depicted in Fig. 9. We also depict the average RMS error curves in the same figure. According to Fig. 9, we discover that the RMS errors resulted from our EM algorithm are much closer to the CRLBs than the SC-ML and AC-ML methods. Note that all the three source localization schemes in comparison are quite sensitive to the initial condition. This still remains as a very challenging problem for the wideband source localization. Note that our experimental results illustrated in this

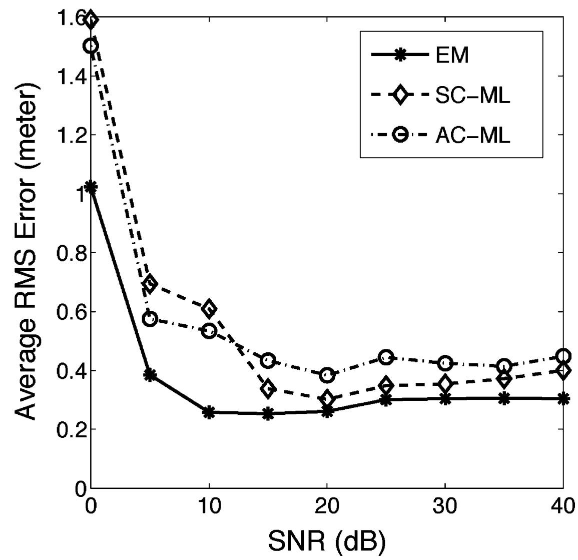

Fig. 6. Average RMS localization errors versus SNR for the sources corrupted by the noises with identical variances. The initial source location estimates are plotted in Fig. 1.

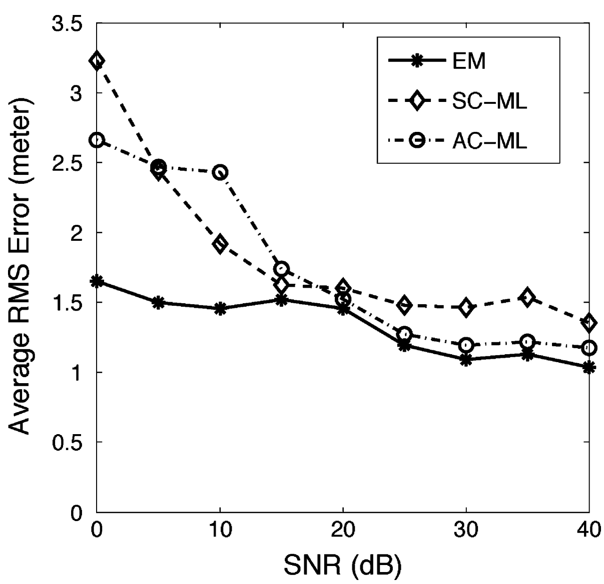

Fig. 7. Average RMS localization errors versus SNR for the sources corrupted by the noises with identical variances. The initial source location estimates are randomly drawn from the areas which are one meter around the initial source location estimates in Fig. 1.

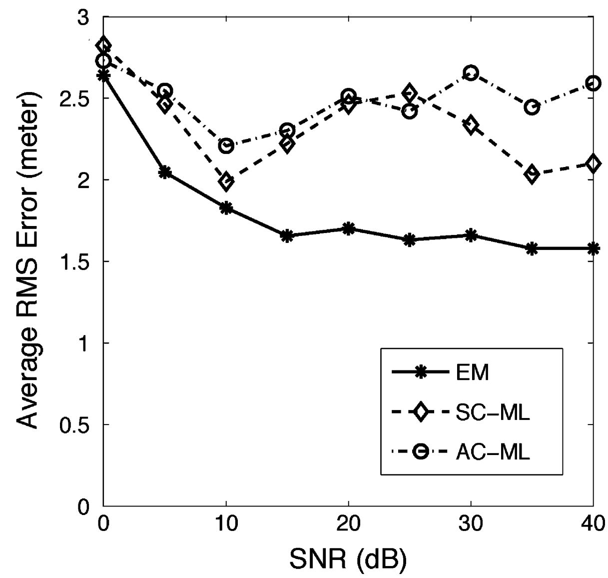

Fig. 8. Average RMS localization errors versus SNR for the sources corrupted by the noises with identical variances. The initial source location estimates are plotted in Fig. 4.

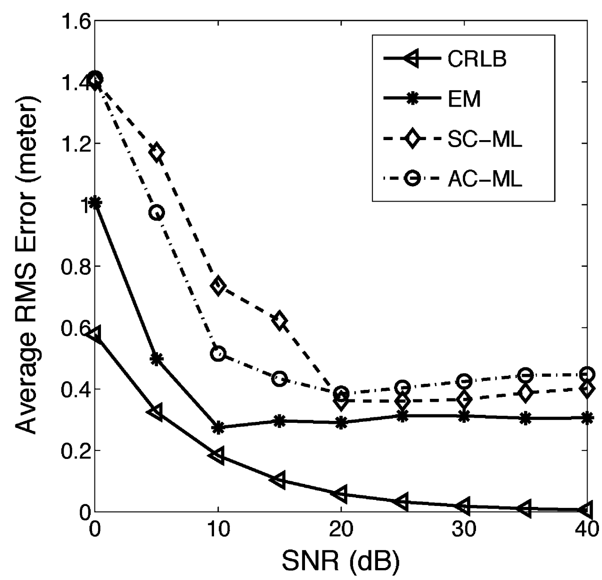

Fig. 9. Cramer–Rao lower bounds and simulated RMS localization errors (actual variances) versus different SNR values for the three schemes in comparison.

paper can be generalized for other conditions. It means that if we change the source locations and use all the three algorithms subject to the same initial conditions, the experimental results under every different condition specified in Sections VI-A–VI-C will be very similar to Figs. 2–9.

VII. Conclusion

In this paper, we propose a novel EM-based multiple wideband source localization scheme in the presence of nonuniform noise variances. For our EM method and the conventional SC-ML and AC-ML methods, the performance is rather sensitive to the initial source location estimates. Our proposed EM algorithm can lead to an outstanding localization performance given a reasonably good initial condition. Moreover, our proposed EM algorithm can always outperform the conventional SC-ML and AC-ML methods when the initial source location estimates are randomly chosen. The Monte Carlo simulation results demonstrate the superiority of our proposed EM method. To provide the robustness analysis for the source localization algorithms, we present the CRLB associated with these three schemes. The CRLB analysis demonstrates that our proposed EM algorithm is much closer to the achievable minimum variance than the two other methods in all SNR conditions. In addition, according to our complexity analysis, the complexity measure for our proposed algorithm is of $\mathcal{O}(M^2)$ which is much less than those for the SC-ML and AC-ML methods [both with a complexity measure of $\mathcal{O}(M^3)$].

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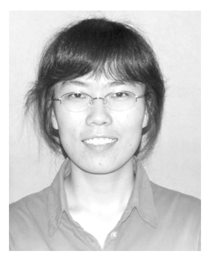

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