AN EXTENDED INFORMATION PF FOR WIDEBAND ACOUSTIC SOURCE TRACKING USING A DISTRIBUTED AVS ARRAY

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ABSTRACT

Consider the problem of tracking multiple acoustic sources in three dimensional (3-D) space using a distributed acoustic vector sensor (AVS) array. Traditionally, indirect approaches are widely used, by which the direction of arrival (DOA) of the source at each sensor is estimated first, and the DOA estimates are then employed to intersect a 3-D position. The performance of position estimation can be seriously degraded by inaccurate DOA estimates at the first stage, and multiple source localization is impossible unless the DOA estimates can be associated to each source accurately. In this paper, a particle filtering (PF) approach is developed to directly fuse the signals collected from distributed sensors and track the 3-D positions. To enhance the tracking performance and keep the computational complexity affordable, an extended information filter is developed to achieve the optimal resampling. The simulations show that the proposed tracking approach significantly outperforms the indirect localization approaches and is able to track multiple active sources accurately.

Index Terms— Acoustic vector sensor, distributed sensor array, Information filter, particle filtering.

1. INTRODUCTION

Acoustic vector sensor (AVS) employs a co-located sensor structure and measures acoustic pressure as well as particle velocity at sensor position [1]. The manifold of an AVS contains both the azimuth and elevation information and enables 2-D DOA estimation. Also the manifold is independent of the source signal frequency, which makes AVS suitable for scenarios where the source signal frequency is wideband or unknown in *a priori*. Due to these merits, both the theoretical aspects and the applications of AVS have been widely studied [1–4]. A full description of AVS in signal processing problems can be found in [1]. Traditional DOA estimation approaches such as Capon beamforming and subspace based approaches using AVSs have been investigated in [2,3]. However, such investigations focus only on the DOA estimation, rather than the 3-D $(x-, y-, z-)$ position estimation.

Recently, advances of distributed sensor arrays in providing unprecedented capabilities for target detection and localization have motivated the deployment of distributed sensor arrays for acoustic source detection and localization [4,5]. In [4], *indirect* approaches have been developed for 3-D source position estimation. At each AVS, Capon beamforming is employed to estimate the DOA of the source. These DOA estimates are then employed to triangulate a 3-D location by using least square based methods. Such approaches assume that the source is static and relatively a large number of snapshots is required to obtain good DOA estimates. Also it can be applied only for single source problem. For multiple sources, a data association method should be employed to associate the DOA estimates with each source.

In this paper, we consider multiple source tracking using a distributed AVS array. A particle filtering (PF) approach is formulated to directly fuse the signals received from all sensors. There is no need to preprocess the data to extract the DOA estimates. Hence, the proposed approach can be referred as a *direct* method. The source motion is modeled by using a constant velocity (CV) model. The likelihood of each particle is constructed by taking the product of the likelihood across all AVSs. To enhance the tracking accuracy and also make the computational complexity affordable, an extended information filter (EIF) is introduced to achieve the optimum importance sampling. The advantages of the proposed approach is that it is able to track dynamic sources and particularly, it can be applied to track multiple wideband acoustic sources. It is worth mentioning that this work can be regarded as an extension of the authors' previous investigation in single AVS based source tracking [6,7].

The rest of this paper is organized as follows. In Section 2, signal model is introduced. Section 3 presents the tracking algorithm developed for acoustic source tracking using distributed AVS array. Simulated experiments are organized in Section 4 and conclusions are drawn in Section 5.

2. SIGNAL MODEL AND INDIRECT METHOD

Assume that multiple wideband acoustic source signals $s_m(t)$, for $m = 1, \dots, M$ impinge on an array equipped with N spatially distributed AVSs at discrete time t. The

2-D DOA of the mth source relative to the nth sensor ($n = 1, \ldots, N$) can be written as $\boldsymbol{\theta}_n^m(t) = [\phi_n^m(t),\ \psi_n^m(t)]^T$ where $\phi_n^m(t) \in (-\pi,\ \pi]$ and $\psi_n^m(t) \in [-\pi/2,\ \pi/2]$ represent the azimuth and elevation angles respectively, and superscript T denotes the transpose. AVS measures acoustic pressure as well as three component particle velocities. Let $\boldsymbol{u}_n^m(t)$ be the unit direction vector pointing from the sensor toward to the source and given as

$$\boldsymbol{u}_n^m(t) = \begin{bmatrix} \cos\psi_n^m(t)\cos\phi_n^m(t) \\ \cos\psi_n^m(t)\sin\phi_n^m(t) \\ \sin\psi_n^m(t) \end{bmatrix}. \tag{1}$$

The received signal at the nth AVS can be modeled as [1]

$$\boldsymbol{y}_n(t) = \sum_{m=1}^{M} \mathbf{a}(\boldsymbol{\theta}_n^m(t))s_m(t) + \boldsymbol{\epsilon}_n(t), \tag{2}$$

where $\mathbf{a}(\boldsymbol{\theta}_n^m(t)) = \left[1, (\boldsymbol{u}_n^m(t))^T\right]^T \in \mathbb{C}^{4\times 1}$ is the steering vector, and $\boldsymbol{\epsilon}_n(t) \in \mathbb{C}^{4\times 1}$ represent the channel noise including the pressure and velocity noise terms. Note that we have normalized the particle velocity terms by multiplying a constant term $-\rho_0 c_0$, where ρ_0 and c_0 represent the ambient density and the propagation speed of the acoustic wave in the medium respectively. For the noise process in (2), it is further assumed that $\boldsymbol{\epsilon}_n(t)$ is a sequence of complex-valued independent and identically distributed (i.i.d.) circular Gaussian random variables with zero mean and covariance matrix $\boldsymbol{\Gamma}$, given as $\boldsymbol{\epsilon}_n(t) \sim \mathcal{CN}(\mathbf{0}, \boldsymbol{\Gamma})$. The distances between the source and the sensors are assumed to be much larger than the maximum wavelength of acoustic signal. Each source signal has an i.i.d. random amplitude $\varepsilon(t)$ and random phase $\zeta(t)$, i.e., $s(t) = \varepsilon(t)e^{j\zeta(t)}$. This means that $s(t)$ is a wide-band signal and is uncorrelated from one snapshot to the next.

Assume that T_0 snapshots are considered at each time step k. When T_0 is small, the source can be assumed stationary and $\boldsymbol{\theta}_n^m(k)$ is used to replace $\boldsymbol{\theta}_n^m(t)$ in the measurement frame. Equation (2) can be written as

$$\mathbf{Y}_n(k) = \mathbf{A}(\boldsymbol{\theta}_n(k))\mathbf{S}(k) + \boldsymbol{\epsilon}_n(k), \tag{3}$$

where $\mathbf{A}(\boldsymbol{\theta}_n(k)) = [\mathbf{a}(\boldsymbol{\theta}_n^1(k)), \ldots, \mathbf{a}(\boldsymbol{\theta}_n^M(k))]$ and $\mathbf{S}(k) = [\mathbf{s}_1(k), \ldots, \mathbf{s}_M(k)]^T$. Capon beamforming response is [2]

$$\mathcal{P}_k^n(\boldsymbol{\theta}) = \left\{\mathbf{A}^H(\boldsymbol{\theta})(\mathbf{R}_k^n)^{-1}\mathbf{A}(\boldsymbol{\theta})\right\}^{-1}, \tag{4}$$

where $\mathbf{R}_k^n$ is the covariance matrix given as

$$\mathbf{R}_k^n = \mathbb{E}\{\mathbf{Y}_n(k)\mathbf{Y}_n(k)^H\} \approx \frac{1}{T_0}\mathbf{Y}_n(k)\mathbf{Y}_n(k)^H, \tag{5}$$

where $\mathbb{E}$ is the expectation operation, and the superscript H denotes the conjugate transpose. The DOA estimation can easily be obtained by implementing a 2-D search over $\boldsymbol{\theta}$ which can maximize the output of Capon beamformer

$$\hat{\boldsymbol{\theta}}_k = \arg \max_{\boldsymbol{\theta}\in(-\pi\ \pi]\times[-\pi/2\ \pi/2]} |\mathcal{P}_k(\boldsymbol{\theta})|, \tag{6}$$

where $|\cdot|$ denotes the amplitude of a complex value. In [4], indirect approaches have been developed for 3-D localization. The DOA measurements at each AVS is estimated first by using (6). The DOAs are then regarded as measurements and employed to triangulate the 3-D source position by using weighted least-square (WL) and re-weighted WL (RWL) approaches. However, such approaches can be used only for single source localization and are easily to be violated by the inaccurate DOA estimates.

In fact, the 3-D source position in Cartesian coordinates are directly related to the received signal. Assume that the nth AVS is deployed at arbitrary locations $\mathbf{x}_n^0 = [x_n^0, y_n^0, z_n^0]^T$ and the m source is located at $\mathbf{x}_{m,k} = [x_{m,k}, y_{m,k}, z_{m,k}]^T$. According to the array geometry, the 2-D DOA $\boldsymbol{\theta}_n^m(k)$ is related to the source position by

$$\begin{aligned} \phi_n^m(k) &= \tan^{-1}\left(\frac{x_{m,k} - x_n^0}{y_{m,k} - y_n^0}\right); \\ \psi_n^m(k) &= \tan^{-1}\left(\frac{z_{m,k} - z_n^0}{\sqrt{(x_{m,k} - x_n^0)^2 + (y_{m,k} - y_n^0)^2}}\right); \end{aligned} \tag{7}$$

Submitting (7) into (2), the relationship between the source position and the received signal can be formulated as

$$\mathbf{Y}_n(k) = \mathbf{A}_n(\mathbf{X}_k)\mathbf{S}(k) + \boldsymbol{\epsilon}_n(k), \tag{8}$$

where $\mathbf{A}_n(\mathbf{X}_k) = [\mathbf{a}_n(\mathbf{x}_{1,k}), \ldots, \mathbf{a}_n(\mathbf{x}_{m,k})]$ and $\mathbf{a}_n(\mathbf{x}_{m,k}) = \mathbf{a}(\boldsymbol{\theta}_n^m(k))$. Equation (8) shows a direct relationship between the measurements and the 3-D positions. In the next section, a particle filtering approach will be developed to estimate the 3-D position of the source directly from the signals collected from all sensors, i.e., $\mathbf{Y}_k = [\mathbf{Y}_1(k), \ldots, \mathbf{Y}_N(k)]^T$.

3. PARTICLE FILTERING FOR DISTRIBUTED AVS ARRAY BASED SOURCE TRACKING

Assume that a measurement sequence $\mathbf{Y}_{1:k} = \{\mathbf{Y}_1, \ldots, \mathbf{Y}_k\}$ until time step k has been obtained. The state to be estimated can be written into a vector $\mathbf{X}_k$ (e.g., $\mathbf{X}_k = [\mathbf{x}_{1,k}^T, \ldots, \mathbf{x}_{M,k}^T]^T$). The posterior distribution of the state $p(\mathbf{X}_k|\mathbf{Y}_{1:k})$ can be obtained via a Bayesian recursive estimation, given as

$$\begin{aligned} p(\mathbf{X}_k|\mathbf{Y}_{1:k-1}) &= \int p(\mathbf{X}_k|\mathbf{Y}_{k-1})p(\mathbf{X}_{k-1}|\mathbf{Y}_{1:k-1})d\mathbf{X}_{k-1}; \\ p(\mathbf{X}_k|\mathbf{Y}_{1:k}) &\propto p(\mathbf{Y}_k|\mathbf{X}_k)p(\mathbf{X}_k|\mathbf{Y}_{1:k-1}). \end{aligned} \tag{9}$$

where $p(\mathbf{X}_{k-1}|\mathbf{Y}_{1:k-1})$ is the posterior distribution at the last time step, and $p(\mathbf{X}_k|\mathbf{Y}_{1:k-1})$ is the prior distribution for the current time step. Since the measurement function is nonlinear, the PF [8] that provides an excellent solution to the nonlinear problem is employed. The core idea of PF is that it uses a set of particles and importance weights of these particles to approximate the posterior distribution. Assuming that L particles $\{\mathbf{X}_k^{(\ell)}, w_k^{(\ell)}\}_{\ell=1}^{L}$ are used to approximate the above

Bayesian recursion. The whole procedure of PF processing can be summarized as following. At time step k, the particles are sampled according to an importance function, given as

$$\mathbf{X}_k^{(\ell)} \sim q(\mathbf{X}_k^{(\ell)}|\mathbf{X}_{k-1}^{(\ell)}, \mathbf{Y}_{1:k}). \tag{10}$$

The importance weights of the particles are then evaluated by

$$w_k^{(\ell)} = w_{k-1}^{(\ell)} \frac{p(\mathbf{Y}_k|\mathbf{x}_k^{(\ell)})p(\mathbf{X}_k^{(\ell)}|\mathbf{X}_{k-1}^{(\ell)})}{q(\mathbf{X}_k^{(\ell)}|\mathbf{X}_{k-1}^{(\ell)}, \mathbf{Y}_{1:k})}, \tag{11}$$

After resampling, the posterior distribution of the state is approximated by $p(\mathbf{X}_k|\mathbf{Y}_{1:k}) \approx \sum_{\ell=1}^{L} \tilde{w}_k^{(\ell)} \delta_{\mathbf{X}_k^{(\ell)}}(\mathbf{X}_k)$, where $\delta(\cdot)$ is a Dirac-delta function, and $\tilde{w}_k^{(\ell)}$ is a normalized weight.

Source dynamics. Assume that the mth source moves with a velocity $\dot{\mathbf{x}}_{m,k} = [\dot{x}_{m,k}, \dot{y}_{m,k}, \dot{z}_{m,k}]^T$. The source state $\mathbf{x}_{m,k}$ can be constructed by cascading the position and velocity parts, i.e., $\mathbf{x}_{m,k} = [\mathbf{x}_{m,k}^T, \dot{\mathbf{x}}_{m,k}^T]^T$. CV model [9] is employed here to model the source dynamics, given as

$$\mathbf{X}_k^{(\ell)} = \mathbf{F}\mathbf{X}_{k-1}^{(\ell)} + \mathbf{G}\mathbf{v}_k, \tag{12}$$

where $\mathbf{v}(k)$ is a zero-mean real Gaussian process (i.e., $\mathbf{v}(k) \sim \mathcal{N}(\mathbf{0}, \mathbf{\Sigma}_\mathrm{v})$. The coefficients $\mathbf{F}$ and $\mathbf{G}$ are defined as

$$\mathbf{F} = \mathbf{I}_M \otimes \begin{bmatrix} \mathbf{I}_3 & \Delta T\mathbf{I}_3 \\ \mathbf{0} & \mathbf{I}_3 \end{bmatrix}; \mathbf{G} = \mathbf{I}_M \otimes \begin{bmatrix} \frac{\Delta T^2}{2}\mathbf{I}_3 \\ \Delta T\mathbf{I}_3 \end{bmatrix}, \tag{13}$$

where ΔT represents the time period between the previous and current time step, and $\otimes$ denotes the Kronecker product. The source state transition density $p(\mathbf{X}_k^{(\ell)}|\mathbf{X}_{k-1}^{(\ell)})$ is determined by the source dynamic model (12).

Optimum importance sampling. Generally, prior importance function is widely employed in PF due to its simplicity. However, the position estimates suffer from large variances. The variance can be minimized by sampling from an optimum importance function, i.e., $\mathbf{X}_k^{(\ell)} \sim p(\mathbf{X}_k^{(\ell)}|\mathbf{X}_{k-1}^{(\ell)}, \mathbf{Y}_k)$. In this paper, an extended information filter (EIF) is introduced to achieve the optimum resampling. To formulate the EIF, the measurement function (8) needs to be linearized first. Applying the first-order Taylor expansion, the measurement function becomes

$$\mathbf{Y}_n(k) \approx \mathbf{H}_k^{n,(\ell)}\mathbf{X}_k^{(\ell)} + \bar{\boldsymbol{\epsilon}}_n(k), \tag{14}$$

where $\bar{\boldsymbol{\epsilon}}_n(k) \sim \mathcal{CN}(\mathbf{0}, \mathbf{P}_k^n)$ is the noise term which includes the measurement noise process as well as the higher order expansion error and $\mathbf{P}_k^n$ is the covariance matrix. $\mathbf{H}_k^{(\ell)}$ is the coefficient matrix of the first-order Taylor expansion given as $\mathbf{H}_k^{n,(\ell)} = \partial\mathbf{A}_n(\mathbf{X}_k^{(\ell)})\mathbf{S}(k)/\partial\mathbf{X}_k^{(\ell)}$ at $\mathbf{X}_k^{(\ell)} = \hat{\mathbf{X}}_{k-1}^{(\ell)}$. EIF can thus be formulated based on the state space model (12) and (14). Assume that the inverse matrix of the state variance is defined as $\mathcal{I}_k = (\mathbf{Q}_k)^{-1}$. The information filter is given by the following equations [10].

$$\begin{aligned}\mathcal{I}_{k|k-1}^{n,(\ell)} =& (\mathbf{Q}_{k-1}^n)^{-1} - (\mathbf{Q}_{k-1}^n)^{-1} \\ & (\mathcal{I}_{k-1}^{n,(\ell)} + (\mathbf{Q}_{k-1}^n)^{-1})^{-1}(\mathbf{Q}_{k-1}^n)^{-1};\end{aligned} \tag{15}$$

$$\mathcal{I}_k^{n,(\ell)} = \mathcal{I}_{k|k-1}^{n,(\ell)} + (\mathbf{H}_k^{n,(\ell)})^H(\mathbf{P}_k^n)^{-1}\mathbf{H}_k^{n,(\ell)} \tag{16}$$

$$\mathcal{K}_k^{n,(\ell)} = (\mathcal{I}_k^n)^{-1}(\mathbf{H}_k^{n,(\ell)})^H(\mathbf{P}_k^n)^{-1} \tag{17}$$

$$\hat{\mathbf{X}}_k^{(\ell)} = \bar{\mathbf{X}}_k^{(\ell)} + \mathcal{K}_k^{n,(\ell)}(\mathbf{Y}_n(k) - \mathbf{H}_k^{n,(\ell)}\bar{\mathbf{X}}_k^{(\ell)}) \tag{18}$$

where $\mathbf{Q}_k^n$ is the covariance matrix for source dynamics. Usually $\mathbf{Q}_k^n$ and $\mathbf{P}_k^n$ are assumed to be a constant, i.e., $\mathbf{Q}_k^n = \mathbf{Q}$ and $\mathbf{P}_k^n = \mathbf{P}$. Therefore the inverse of $\mathbf{Q}_k^n$ and $\mathbf{P}_k^n$ can be calculated once at the beginning of the algorithm, not at each iteration. The matrix to be inverted is thus only the information matrix $\mathcal{I}_k^{n,(\ell)}$, which is of a size $6M \times 6M$. Hence, the computation complexity for the inverse operation of EIF is significantly lower than that of EKF (in EKF, the matrix to be inverted is often with a size of the square of measurement size, i.e., $4T_0 \times 4T_0$). After each EIF implementation, the PDF of particles is a Gaussian distribution with mean $\hat{\mathbf{X}}_k^{(\ell)}$ and covariance matrix $(\mathcal{I}_k^{n,(\ell)})^{-1}$, given as

$$p(\mathbf{X}_k^{(\ell)}|\mathbf{X}_{k-1}^{(\ell)}, \mathbf{Y}_n(k)) = \mathcal{N}(\mathbf{X}_k^{(\ell)}; \hat{\mathbf{X}}_k^{(\ell)}, (\mathcal{I}_k^n)^{-1}). \tag{19}$$

Hence, the optimum importance function at each time step is $q(\cdot) = p(\mathbf{X}_k^{(\ell)}|\mathbf{X}_{k-1}^{(\ell)}, \mathbf{Y}_N(k))$.

Concentrated likelihood (CL). Since the measurement noise process is assumed to be Gaussian, the likelihood function at each individual AVS can be written as

$$\begin{aligned}\mathcal{L}(\mathbf{Y}_n(k)|\mathbf{X}_k^{(\ell)}) =& (\pi^{-4T})\det(\pi\Gamma_k)^{-T_0} \\ & \exp\Big\{ - T_0\mathrm{tr}\big(\Gamma_k^{-1}\mathbf{R}_k^n\big)\Big\},\end{aligned} \tag{20}$$

where $\det(\cdot)$ and $\mathrm{tr}(\cdot)$ represent the determinant and trace operation respectively. The statistics of source signal and noise process are unknown in practice. CL function is thus employed, by which these parameters are estimated based on a maximum likelihood estimator. CL function is given by [1]

$$\begin{aligned}p(\mathbf{Y}_n(k)|\mathbf{X}_k^{(\ell)}) =& (\pi^{-4T_0})\exp(-4T_0) \\ & \det(\mathbf{\Pi}_k^n\mathbf{R}_k^n\mathbf{\Pi}_k^n + \hat{\sigma}_n^2\mathbf{\Pi}_k^{n,0})^{-T_0}\end{aligned} \tag{21}$$

where

$$\mathbf{\Pi}_k^n = \mathbf{A}_n(\mathbf{X}_k^{(\ell)})(\mathbf{A}_n^H(\mathbf{X}_k^{(\ell)})\mathbf{A}_n(\mathbf{X}_k^{(\ell)}))^{-1}\mathbf{A}_n^H(\mathbf{X}_k^{(\ell)});$$

$$\mathbf{\Pi}_k^{n,0} = \mathbf{I} - \mathbf{\Pi}_k^n; \quad \hat{\sigma}_n^2 = \frac{1}{4-M}\mathrm{tr}(\mathbf{\Pi}_k^{n,0}\mathbf{R}_k^n).$$

According to our assumption that the channel noise for each AVS is independent. The total likelihood is thus

$$p(\mathbf{Y}_k|\mathbf{X}_k^{(\ell)}) = \prod_{n=1}^{N} p(\mathbf{Y}_n(k)|\mathbf{X}_k^{(\ell)}) \tag{22}$$

Hence, after the importance sampling (19), the likelihood can be evaluated according to (22). The position estimates can also be obtained by implementing a 3-D search over the possible source location area which maximizes (21). However,

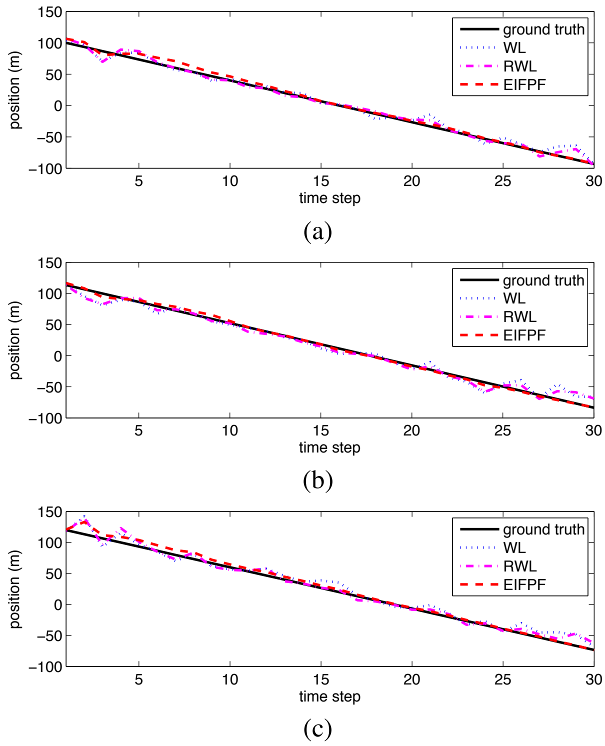

Fig. 1. Single source estimation results under SNR $= 4$dB and $T_0 = 8$ for (a) $x-$; (b) $y-$; and (c) $z-$ coordinate.

such a method is computationally very expensive since a 3-D search is required.

For initialization, the particles are drawn according to a Gaussian distribution around a coarse position estimation, i.e., $\mathbf{X}_0^{(\ell)} \sim \mathcal{N}(\mathbf{X}_0^{(\ell)}; \bar{\mathbf{X}}_0, \mathbf{\Sigma}_0)$ where $\bar{\mathbf{X}}_0$ is the estimated position and $\mathbf{\Sigma}_0$ is the variance of initial distribution which characterizes the error of initial position estimates. The advantages of the proposed approach is that it does not require a 2-D search to obtain the DOA estimates and all the signals are directly fused to estimate the source position. Also, it can be employed for multiple source tracking.

4. SIMULATIONS

Six sensors are deployed to formulate a distributed AVS array. The sensor locations are: (30,−26,40.39)m, (60,−21, 169.95)m, (0,0,0)m, (40,38,−10.57)m, (−65,40,−5.43) m, and (−100,−10,51.80)m. Such a sensor deployment is exactly the same as that in [4]. Two sets of simulations are of our interests: single source tracking and multiple source tracking. For the former one, the tracking performance of the proposed extended information filter based particle filtering (EIFPF) is compared with that using the approaches in [4], i.e., WL and RWL methods. For the latter case, we only present the tracking results and performance analysis of the proposed approach since WL and RWL approaches cannot

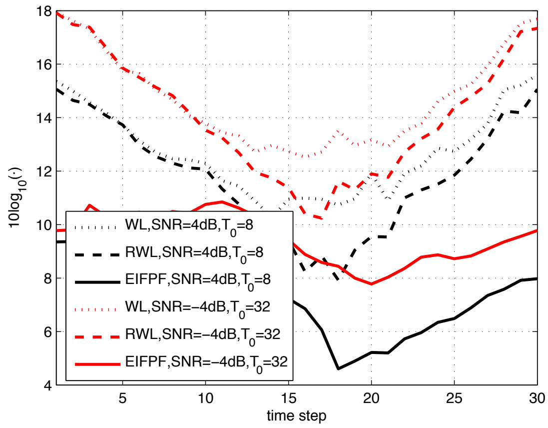

Fig. 2. Single source scenario: RMSE for 100 MC runs.

be employed for multiple source localization scenario. The background noise level is evaluated by SNR, and is simulated by adding the complex circular i.i.d. Gaussian noise into the received signal. The parameters for EIFPF are set as: $L = 500, \mathbf{\Sigma}_0 = 100\mathbf{I}_{3M}, \mathbf{\Sigma}_v = 0.01\mathbf{I}_{3M}$, and $\mathbf{P} = 0.02\mathbf{I}_{4T_0}$. This parameter setup is found adequate for all following experiments. The source velocities are initialized around the ground truth. The initial positions are coarsely estimated by maximize the likelihood function (22).

In the first simulation, a single source that is active from $(100, 113, 120)$m to $(-100, -90, -80)$m with 30 time steps is considered. Each time step is assumed to be 1 second. The source thus moves with a velocity of 7m/sec. roughly along all coordinates. Fig. 1 shows the 3-D position estimation results from a single implementation under SNR $= 4$dB and $T_0 = 8$. The proposed EIFPF approach is able to converge and lock on to the ground truth trajectories quickly, and therefore consistently track the source positions. It performs much better than WL and RWL based indirect localization approaches. Multiple Monte Carlo (MC) implementations are also organized to further illustrate the tracking performance. Fig. 2 presents the average root mean square error (RMSE) over 100 MC runs under SNR $= 4$dB, $T_0 = 8$ and SNR $= -4$dB, $T_0 = 32$. The proposed EIFPF approach significantly outperforms the indirect localization approaches under all simulated scenarios. Also, it can be observed that RWL approach performs better than WL approach. It is worth mentioning that the RMSE is relatively smaller at the middle of the tracking period since the source is closer to the distributed AVS array at these time steps.

In the second simulation, two simultaneously active sources are considered: one (S1) is active from $(-10, -43, -120)$m to $(-100, 60, -20)$m, and the other (S2) from $(10, 80, 20)$m to $(110, -20, 120)$m with 30 time steps. Such motions result in a velocity of ± 3.5m/sec. roughly. Fig. 3 shows the results from a single implementation under

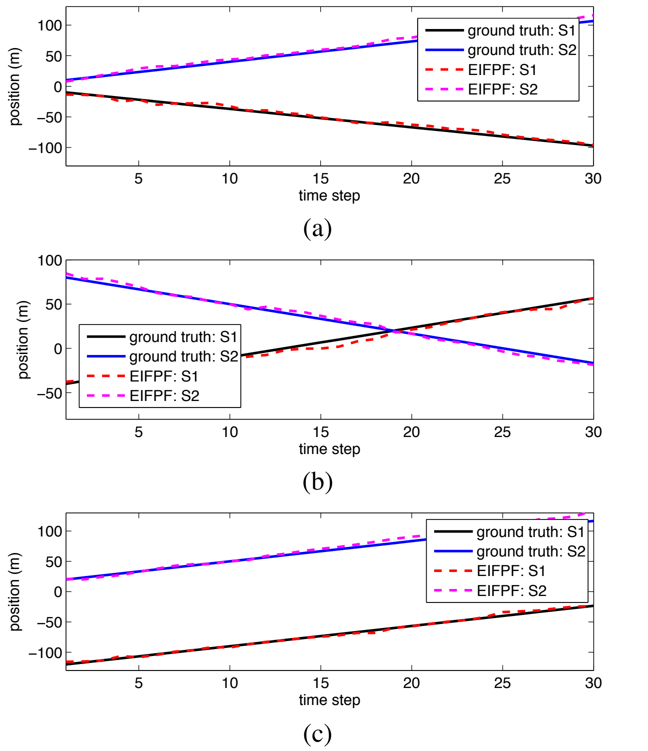

Fig. 3. Multiple source estimation results under SNR $= 4$dB and $T_0 = 8$ for (a) $x-$; (b) $y-$; and (c) $z-$ coordinate.

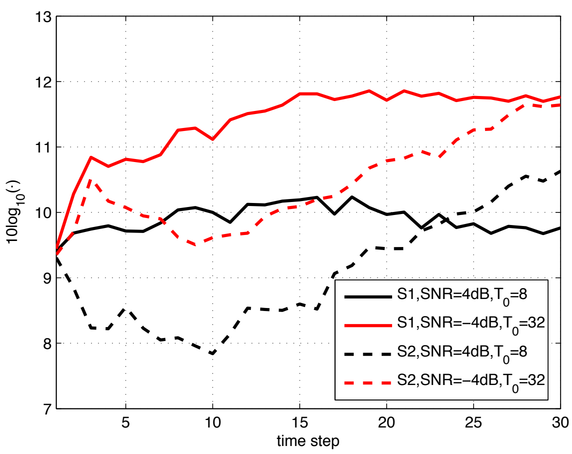

Fig. 4. Multiple source scenario: RMSE for 100 MC runs.

SNR $= 4$dB and $T_0 = 8$. The proposed tracking approach is able to track the trajectories of the two sources accurately. Even though the two sources are closely spaced at the initial steps along with $x-$ coordinate and cross over along with $y-$ coordinate, the algorithm can still lock on to the source trajectories. The RMSE over 100 MC runs under SNR $= 4$dB, $T_0 = 8$ and SNR $= -4$dB, $T_0 = 32$ is presented in Fig. 4. It shows that the direct tracking approach is able to provide good accuracy for 3-D location estimation for multiple simultaneously active sources. As the single source scenario, when the source approaches to the array, better accuracy can be achieved, and vice versa.

5. CONCLUSIONS

A PF approach for 3-D source tracking using a distributed AVS array is developed. The proposed approach is able to directly fuse the information from all sensors to estimate the position. To enhance the tracking accuracy, an EIF is developed to achieve the optimal resampling, and meanwhile to keep the computational complexity affordable. The simulations show that the proposed tracking approach significantly outperforms the indirect localization approach and is able to track multiple simultaneously active sources accurately. The application of the proposed approach in real acoustic environments such as room and underwater acoustic source tracking will be considered in our future work.

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