PARTICLE FILTERING FOR 2-D DIRECTION OF ARRIVAL TRACKING USING AN ACOUSTIC VECTOR SENSOR

Xionghu Zhong, Premkumar A. B, and A. S. Madhukumar

Centre for Multimedia and Network Technology, School of Computer Engineering,
College of Engineering, Nanyang Technological University, 639798, Singapore.
{xhzhong, asannamalai, and asmadhukumar}@ntu.edu.sg

ABSTRACT

Acoustic vector sensor (AVS) signal measures acoustic pressure as well as particle velocity, and therefore contains both the azimuth and the elevation information of the source. Existing 2-D DOA estimation methods for AVS assume that the source is static and extensively rely on the localization techniques. In this paper, a particle filtering (PF) approach is developed to track the 2-D DOA by using a single AVS. A constant velocity model is employed to model the source dynamics and the likelihood function is derived based on maximum likelihood estimation of the source amplitude and the noise variance. Since the likelihood function is usually spread and distorted in the heavy noisy environment, it is further exponentially weighted to enhance the weight of particles at high likelihood area. Simulations show that the proposed algorithm significantly outperforms the traditional Capon beamforming method and is able to lock on the DOA of the source in challenging environments.

1. INTRODUCTION

Localizing the 2-D (azimuth and elevation) direction of arrival (DOA) of an acoustic source in a noisy environment plays an important role in many applications such as speech, seismology, sonar and radar. It is usually achieved by using arrays with several pressure sensors, together with estimation techniques based on the collected pressure measurements [1]. Acoustic vector sensor is a new technology developed in the recent past to measure the acoustic pressure as well as three components ($x-$, $y-$ and $z-$ coordinates) of the particle velocity [2]. Compared to the traditional pressure sensor, it produces additional information that enables 2-D DOA estimation unambiguously with a single vector sensor.

Theoretical aspects and practical applications of AVS have been extensively studied [2, 3]. DOA estimation using a single AVS and corresponding performance study are investigated in [3–5]. However, these analysis are based on the *localization* techniques such as beamforming and MUSIC [3, 6], in which the source is assumed to be static and only spatial information from current measurements are employed. In real applications, the sources (e.g., submarines or robots) are in fact dynamic and moving smoothly. The DOAs are highly correlated within adjacent time steps. Hence, it is desired to exploit the information from both the previous DOA estimates and the current measurements to localize the source. DOA estimation via *tracking* is such an approach where previous estimates can be fed back into the system for subsequent estimations. Among all tracking approaches, particle filtering (PF) [7] is found effective in coping with nonlinear and non-Gaussian system models and has been successfully used for underwater acoustic source tracking problem [8, 9].

In this paper, a PF is formulated to track the 2-D DOA of an acoustic source using an AVS. Since the movement of the underwater source can be assumed to be smooth, the constant velocity (CV) model [10] is used to model the source dynamics. The measurement equation is the AVS data model which is nonlinear function of the source state. The source amplitude and the variance of measurement noise process are unknown in practice. These parameters are thus estimated by using a maximum likelihood estimator. The likelihood of particles are then derived. Since the mainlobe of the spectra is spread by low signal-to-noise (SNR) environment, the likelihood function is further exponentially weighted to generate a sharper peak and to emphasize the particles sampled at high likelihood area. Due to a sample-based representation of the posterior probability density function (PDF) of the state vector, PF is well suited for DOA estimation based on the nonlinear measurement equation. The key advantage of the proposed tracking algorithm is its ability to estimate the DOA accurately and efficiently when the source motion is unknown *a priori* in a low SNR environment.

The rest of this paper is organized as follows. In Section 2, the AVS signal model and Capon beamforming method are introduced. Section 3 presents the source motion and likelihood models. The enhanced likelihood model and the tracking algorithm are also formulated. Simulated experiments are organized in Section 4 and conclusions are drawn in Section 5.

2. AVS SIGNAL MODEL AND CAPON BEAMFORMING

Consider a narrow band acoustic source $s(t)$, with a center frequency f_0, impinging on an AVS. The source emits signal at a 2-D direction given by

$$\boldsymbol{\theta}_t = [\phi_t,\ \psi_t]^T, \tag{1}$$

where $\phi_t \in (0,\ 2\pi]$ and $\psi_t \in [-\pi/2,\ \pi/2]$ denotes the azimuth and the elevation respectively, and t is the time instance.

Let $\boldsymbol{v}(\boldsymbol{r}, t)$ denote the particle velocity of acoustic wave at a position $\boldsymbol{r}$, and $p(\boldsymbol{r}, t)$ be the acoustic pressure. Here $\boldsymbol{v}(\boldsymbol{r}, t), \boldsymbol{r} \in \mathbb{R}^3$, and $p(\boldsymbol{r}, t) \in \mathbb{R}$. The relationship between the acoustic pressure and the particle

© EURASIP, 2011 - ISSN 2076-1465

velocity is given by [2],

$$\boldsymbol{v}(\boldsymbol{r},t) = -p(\boldsymbol{r},t)\boldsymbol{u}_t/(\rho_0 c), \tag{2}$$

where ρ_0 is the ambient pressure, and c is the propagation speed of the acoustic wave in the medium. $\boldsymbol{u}_t$ is the unit direction given by

$$\boldsymbol{u}_t = [\cos\psi_t \cos\phi_t, \cos\psi_t \sin\phi_t, \sin\psi_t]^T, \tag{3}$$

where the superscript T denotes the matrix transpose.

Further assume that a single AVS is located at $\boldsymbol{r}$, which is known and is fixed during all time steps. The acoustic pressure and particle velocity will only depend on the time t. Using the phasor representation, the plan wave signal model can be written as

$$\mathbf{y}(t) = \begin{bmatrix} 1 \\ -\frac{1}{\rho_0 c}\boldsymbol{u}_t \end{bmatrix} e^{-j2\pi f_0 \tau_t} s(t) + \begin{bmatrix} \mathrm{n}_p(t) \\ \mathbf{n}_v(t) \end{bmatrix}, \tag{4}$$

where $s(t) \in \mathbb{C}$ is the complex pressure envelope of the source signal, and $\mathrm{n}_p(t) \in \mathbb{C}$ and $\mathbf{n}_v(t) \in \mathbb{C}^{3\times 1}$ represent the corresponding pressure and velocity noise terms respectively. τ_t is the time delay of the plane wave from the source to the sensor, i.e., $\tau_t = -\boldsymbol{r}^T\boldsymbol{u}_t/c$. For a target which moves relatively slow, the DOA $\boldsymbol{\theta}_t$ can be assumed to be stable if a small number of snapshots are processed at each time step. Assume that N snapshots are taken into account at time step k, and let

$$\mathbf{s}(k) = [s(kN+1), \ldots, s(kN+N)], \tag{5}$$

denote the snapshots of the source signal ($\mathbf{s}(k) \in \mathbb{C}^{1\times N}$). The noise and received data can be written as

$$\mathbf{N}(k) = [\mathbf{n}(kN+1), \ldots, \mathbf{n}(kN+N)]; \tag{6}$$

$$\mathbf{Y}(k) = [\mathbf{y}(kN+1), \ldots, \mathbf{y}(kN+N)], \tag{7}$$

where $\mathbf{N}(k), \mathbf{Y}(k) \in \mathbb{C}^{4\times N}$. Accordingly, θ_k is used to express the DOA at time step k. Equation (4) can thus be written as

$$\mathbf{Y}(k) = \mathbf{a}(\boldsymbol{\theta}_k) \otimes \mathbf{s}(k) + \mathbf{N}(k), \tag{8}$$

where

$$\mathbf{a}(\boldsymbol{\theta}_k) = e^{-j2\pi f_0 \tau_k}\boldsymbol{h}(\boldsymbol{\theta}_k), \tag{9}$$

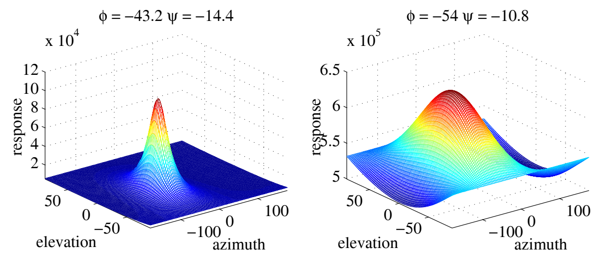
is the steer vector with $\boldsymbol{h}(\boldsymbol{\theta}_k) = [1, -\boldsymbol{u}_k^T/(\rho_0 c)]^T$ denoting the AVS response at coordinate origin, and $\otimes$ denotes the Kronecker product. The received signal includes both the the azimuth and elevation information, and can be used for 2-D DOA estimation.

The noise term $\mathbf{N}(k)$ in (8) is assumed to be independent identically distributed (i.i.d.) zero-mean complex circular Gaussian processes and are independent from different channels. Also the source signal $\mathbf{s}(k)$ and the noise $\mathbf{N}(k)$ are uncorrelated. The PDF of the measurements can be written as

$$\mathbf{Y}(k) \sim \mathcal{CN}(\cdot|\mathbf{a}(\boldsymbol{\theta}_k) \otimes \mathbf{s}(k), \boldsymbol{\Gamma}_k), \tag{10}$$

where $\mathcal{CN}(\cdot|\boldsymbol{\mu}, \boldsymbol{\Sigma})$ represents a multivariate complex Gaussian distribution with mean $\boldsymbol{\mu}$ and covariance matrix $\boldsymbol{\Sigma}$. The covariance matrix $\boldsymbol{\Gamma}_k$ is given as

$$\boldsymbol{\Gamma}_k = \begin{bmatrix} \sigma_p^2 & \mathbf{0} \\ \mathbf{0} & \sigma_v^2 \mathbf{I}_3 \end{bmatrix}, \tag{11}$$



(a) (b)

Figure 1: Response of the Capon beamforming under the environments (a) SNR = 10dB; (b) SNR = −10dB. The source signal is located at $(-44.4°, -14.4°)$. The estimated DOA is labeled at the top of each figure.

where $\mathbf{I}_m$ is an mth order identity matrix, and σ_p^2 and σ_v^2 are the noise variances for the pressure and velocity components respectively. The Capon spectra estimation for signal model given in (8) is computed according to [3]

$$\mathcal{P}_k(\boldsymbol{\theta}) = \{\mathbf{a}^H(\boldsymbol{\theta})\mathbf{R}_k^{-1}\mathbf{a}(\boldsymbol{\theta})\}^{-1}, \tag{12}$$

where the superscript H denotes the conjugate transposition and $\mathbf{R}_k$ is the covariance matrix given as,

$$\begin{aligned} \mathbf{R}_k &= \mathbb{E}\{\mathbf{Y}(k)\mathbf{Y}(k)^H\} \\ &= \mathbf{a}(\boldsymbol{\theta}_k)\mathbf{P}_k\mathbf{a}^H(\boldsymbol{\theta}_k) + \boldsymbol{\Gamma}_k, \end{aligned} \tag{13}$$

with $\mathbb{E}\{\cdot\}$ denoting the expectation operation. The DOA estimation can easily be obtained by implementing a 2-D search over the potential $\boldsymbol{\theta}$ which maximizes the output of Capon beamformer, stated as

$$\hat{\boldsymbol{\theta}}_k = \arg \max_{\boldsymbol{\theta} \in [-\pi\ \ \pi]\times[-\pi/2\ \ \pi/2]} |\mathcal{P}_k(\boldsymbol{\theta})|. \tag{14}$$

where $|\cdot|$ denotes the amplitude of a complex value. Capon beamformer is widely used for DOA estimation due to its simplicity and efficiency in suppressing the effect of noise. In noisy environments where the signal to noise ratio (SNR) is relatively high, Capon spectra is able to present the source DOA by a sharp peak as shown in Fig.1(a). However, when the SNR is low, the peak may be distorted and the estimated DOA may be far away from the ground truth, as shown in Fig. 1(b).

3. DOA ESTIMATION VIA PARTICLE FILTERING

To formulate the general framework for DOA tracking problem, the state-space model has to be defined first. Consider that a source is currently at DOA $\boldsymbol{\theta}_k$ and moving with a velocity $\dot{\boldsymbol{\theta}}_k$ (in rad/s). The source state $\mathbf{x}_k$ can thus be constructed by the DOA $\boldsymbol{\theta}_k$ and the motion velocity $\dot{\boldsymbol{\theta}}_k$, i.e., $\mathbf{x}_k = [\boldsymbol{\theta}_k, \dot{\boldsymbol{\theta}}_k]^T$. The CV model [10] is used here to model the source dynamics, given as

$$\mathbf{x}_k = \mathbf{A}\mathbf{x}_{k-1} + \mathbf{B}\mathbf{v}_k, \tag{15}$$

where the coefficient matrix $\mathbf{A}$ and $\mathbf{B}$ are defined by

$$\mathbf{A} = \begin{bmatrix} \mathbf{I}_2 & \Delta T\mathbf{I}_2 \\ \mathbf{0} & \mathbf{I}_2 \end{bmatrix}; \ \mathbf{B} = \begin{bmatrix} \Delta T^2/2\mathbf{I}_2 \\ \Delta T\mathbf{I}_2 \end{bmatrix}, \tag{16}$$

with ΔT representing the time period in seconds between the previous and current time step, and $\mathbf{v}(k)$ is a zero-mean real Gaussian process (i.e., $\mathbf{v}(k) \sim \mathcal{N}(\mathbf{0}, \mathbf{\Sigma}_k)$ with $\mathbf{\Sigma}_k = \mathrm{diag}(\sigma_\phi^2, \sigma_\psi^2)$) used to model the turbulence on the source velocity. Here $\mathrm{diag}(C)$ represents a diagonal matrix with main diagonal entry C.

A natural choice for the measurement function is the AVS data model given in (8). Let $\mathbf{Y}_{1:k} = \{\mathbf{Y}_1, \ldots, \mathbf{Y}_k\}$ denote all the measurements obtained up to time step k. The task here is to estimate the posterior $p(\mathbf{x}_k|\mathbf{Y}_{1:k})$ recursively. The solution based on Bayesian recursive estimation towards to this problem can be given as

- Predict:

$$p(\mathbf{x}_k|\mathbf{Y}_{1:k-1}) = \int p(\mathbf{x}_k|\mathbf{x}_{k-1})p(\mathbf{x}_{k-1}|\mathbf{Y}_{1:k-1})d\mathbf{x}_{k-1}; \tag{17}$$

- Update:

$$p(\mathbf{x}_k|\mathbf{Y}_{1:k}) \propto p(\mathbf{Y}_k|\mathbf{x}_k)p(\mathbf{x}_k|\mathbf{Y}_{1:k-1}). \tag{18}$$

In this recursion, $p(\mathbf{x}_{k-1}|\mathbf{Y}_{1:k-1})$ is the posterior distribution estimated at the last time step, and $p(\mathbf{x}_k|\mathbf{Y}_{1:k-1})$ is the prior distribution for the current time step. The Bayesian recursion states that given the posterior distribution of the state estimated at the previous time step $k-1$ and system models, the current probability distribution of the state can be obtained recursively. Although Kalman filter can be used to solve the Bayesian recursion in (17) and (18), its usage is limited in the case of linear and Gaussian system models. Here, the PF that provides an excellent solution to the nonlinear problem is employed [7]. Given the state particles $\mathbf{x}_{k-1}^{(\ell)}$, for $\ell = 1, \ldots, L$ at previous time step $k-1$, the transition density $p(\mathbf{x}_k^{(\ell)}|\mathbf{x}_{k-1}^{(\ell)})$ is given by the source dynamic model (15), that is

$$p(\mathbf{x}_k^{(\ell)}|\mathbf{x}_{k-1}^{(\ell)}) = \mathcal{N}(\mathbf{x}_k^{(\ell)}|\mathbf{A}\mathbf{x}_{k-1}^{(\ell)}, \mathbf{B}\mathbf{\Sigma}_k\mathbf{B}^T). \tag{19}$$

The particles are thus sampled based on the prior importance function which is determined by the above source dynamic model. Under such a sampling scheme, the particles are weighted according to the likelihood of each particle, given as

$$w_k^{(\ell)} = \tilde{w}_{k-1}^{(\ell)} p(\mathbf{Y}_k|\mathbf{x}_k^{(\ell)}), \tag{20}$$

where $\tilde{w}_{k-1}^{(\ell)}$ is the normalized weight at the last time step. The task here is thus deriving the likelihood according to the AVS data model (8). Since the measurement noise process is assumed to be Gaussian, the likelihood function can be written as

$$\begin{aligned}\mathcal{L}(\mathbf{Y}_k|\mathbf{x}_k^{(\ell)}) =& (\det \pi \mathbf{\Gamma}_k)^{-1} \\ & \exp\{-\mathrm{Tr}([\mathbf{Y}(k) - \mathbf{a}(\mathbf{C}\mathbf{x}_k^{(\ell)}) \otimes \mathbf{s}(k)]^H \\ & \mathbf{\Gamma}_k^{-1}[\mathbf{Y}(k) - \mathbf{a}(\mathbf{C}\mathbf{x}_k^{(\ell)}) \otimes \mathbf{s}(k)])\}.\end{aligned} \tag{21}$$

where $\mathbf{C} = [\mathbf{1}\ \mathbf{0}]$ such that $\mathbf{C}\mathbf{x}_k$ outputs the DOA part of the state, and $\det(\cdot)$ denotes the determinant, and $\mathrm{Tr}(\cdot)$ represents the trace operation. Since the source signal $\mathbf{s}(k)$ and the variance matrix $\mathbf{\Gamma}_k$ of measurement noise processes are unknown in practice, they are estimated by using a maximum likelihood estimator. The analytic solutions are obtained by solving the gradient equations $\partial \ln \mathcal{L}(\mathbf{Y}_k|\mathbf{x}_k^{(\ell)})/\partial \mathbf{s}(k) = 0$ and $\partial \ln \mathcal{L}(\mathbf{Y}_k|\mathbf{x}_k^{(\ell)})/\partial \mathbf{\Gamma}_k = 0$ respectively. For brevity, we only present the results as follows

$$\hat{\mathbf{s}}(k) = \frac{\mathbf{a}^H(\mathbf{C}\mathbf{x}_k^{(\ell)})\mathbf{Y}_k}{\mathbf{a}^H(\mathbf{C}\mathbf{x}_k^{(\ell)})\mathbf{a}(\mathbf{C}\mathbf{x}_k^{(\ell)})}; \tag{22}$$

$$\hat{\mathbf{\Gamma}}(k) = \mathbf{R}_k - \frac{\mathbf{a}(\mathbf{C}\mathbf{x}_k^{(\ell)})\mathbf{a}^H(\mathbf{C}\mathbf{x}_k^{(\ell)})\mathbf{R}_k}{\mathbf{a}^H(\mathbf{C}\mathbf{x}_k^{(\ell)})\mathbf{a}(\mathbf{C}\mathbf{x}_k^{(\ell)})}. \tag{23}$$

Inserting the maximum likelihood estimation $\hat{\mathbf{s}}(k)$ and $\hat{\mathbf{\Gamma}}(k)$ back into the equation (21), the likelihood for the interested parameters can be addressed as

$$\begin{aligned}&\hat{p}(\mathbf{Y}_k|\mathbf{x}_k^{(\ell)}) = \\ &\left\{\frac{1}{e^N \pi^4}\right\}\left\{\det\left(\mathbf{I} - \frac{\mathbf{a}(\mathbf{C}\mathbf{x}_k^{(\ell)})\mathbf{a}^H(\mathbf{C}\mathbf{x}_k^{(\ell)})}{\mathbf{a}^H(\mathbf{C}\mathbf{x}_k^{(\ell)})\mathbf{a}(\mathbf{C}\mathbf{x}_k^{(\ell)})}\right)\mathbf{R}_k\right\}^{-1};\end{aligned} \tag{24}$$

Due to low SNR noisy environment, the mainlobe of the likelihood function is usually spread and spurious peaks may appear. the likelihood function (24) is normalized and exponentially weighted as

$$p(\mathbf{Y}_k|\mathbf{x}_k^{(\ell)}) = \left\{\frac{\hat{p}(\mathbf{Y}_k|\mathbf{x}_k^{(\ell)})}{\max_{\mathbf{x}_k^{(\ell)}} \hat{p}(\mathbf{Y}_k|\mathbf{x}_k^{(\ell)})}\right\}^r, \tag{25}$$

with $r \in \mathbb{R}^+$. After this weighting, the likelihood function is reshaped to enhance the weight of particles sampled at high likelihood area. This step is very important since it is able to help the subsequent resampling algorithm to select and replicate the particles more efficiently. Given the transition and likelihood models derived above, the PF algorithm for AVS source tracking is described in Algorithm 1. Since the initial DOA is unknown, the particles for the DOA state are initialized as a uniform distribution over the possible DOA range, given as

$$\boldsymbol{\theta}_0^{(\ell)} \sim \mathcal{U}_\phi[-\pi,\ \pi] \times \mathcal{U}_\psi[-\pi/2,\ \pi/2], \tag{26}$$

where $\mathcal{U}_d[a, b]$ is a uniform distribution over the possible range $[a, b]$ for variable d. The velocity part of the state $\dot{\boldsymbol{\theta}}_0^{(\ell)}$ are initialized as a Gaussian distribution with the covariance matrix $\mathbf{\Sigma}_0$ around the actual velocity $\mathbf{v}_0$, i.e., $\dot{\boldsymbol{\theta}}_0^{(\ell)} \sim \mathcal{N}(\cdot|\mathbf{v}_0, \mathbf{\Sigma}_0)$.

The PF algorithm described in Algorithm 1 is developed for narrowband acoustic source tracking. However, its extension to wideband acoustic source tracking scenarios is straightforward. The likelihood model of wideband acoustic signal is a production of the likelihood of each frequency component as described in (21). Consequently, the likelihood of particles $p(\mathbf{Y}_k|\mathbf{x}_k^{(\ell)})$ can be obtained by taking the production of the likelihood over all frequencies in (24).

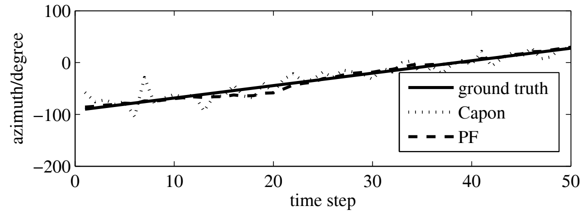
Algorithm 1: PF for AVS 2-D DOA tracking.

Initialisation: for $\ell = 1, \ldots, L$, draw particles
$\boldsymbol{\theta}_0^{(\ell)} \sim \mathcal{U}[-\pi,\ \pi] \times \mathcal{U}[-\pi/2,\ \pi/2]$;
$\dot{\boldsymbol{\theta}}_0^{(\ell)} \sim \mathcal{N}(\cdot|\mathbf{v}_0, \boldsymbol{\Sigma}_0)$;
set the initial weight $\tilde{w}_0^{(\ell)} = 1/L$;
for $k \leftarrow 1$ **to** K **do**
  for $\ell \leftarrow 1$ **to** L **do**
    - draw particles $\boldsymbol{\theta}_k^{(\ell)}$ according to (19);
    - compute the likelihood $\hat{p}(\mathbf{Y}_k|\mathbf{x}_k^{(\ell)})$ from (24);
    - compute the enhanced likelihood $p(\mathbf{Y}_k|\mathbf{x}_k^{(\ell)})$ according to (25);
    - compute the importance weight:
$$w_t^{(\ell)} = \tilde{w}_{t-1}^{(\ell)} p(\mathbf{Y}_k|\mathbf{x}_k^{(\ell)});$$
  end
  normalise the weight: $\tilde{w}_k^{(\ell)} = w_k^{(\ell)} / \sum_{\ell=1}^{L} w_k^{(\ell)}$;
  resample the particles according to the high/low weights;
  output the estimates $\hat{\boldsymbol{\theta}}_k = \sum_{\ell=1}^{L} \tilde{w}_k^{(\ell)} \mathbf{C}\mathbf{x}_k^{(\ell)}$.
end

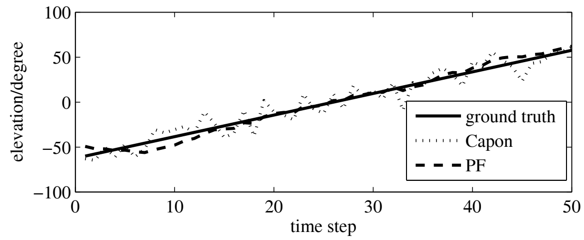
4. SIMULATION EXPERIMENTS

A single AVS located at the origin is used as the receiver, i.e., $\boldsymbol{r} = [0, 0, 0]^T$. The source signal is generated by a complex sinusoid with the frequency of 50Hz. The sampling frequency is 1kHz. The source starts from time step 1 to 50, with the corresponding DOA $(-90°, -60°)$ and $(30°, 60°)$ respectively. The source is thus moving with a velocity of 2°/sec. roughly along both the azimuth and elevation directions. The background noise level is evaluated by SNR, and is simulated by adding the white Gaussian noise (WGN) into the received signal. The tracking performance of proposed PF tracking approach is compared with that of Capon beamforming method. The Capon spectra is estimated from 100×100 grids in the 2-D DOA space. The parameters for PF are set as: $\mathbf{v}_0 = [0.01\ 0.01]^T$, $\boldsymbol{\Sigma}_0 = \mathrm{diag}(4 \times 10^{-4}, 4 \times 10^{-4})$, and $\sigma_\phi^2 = \sigma_\psi^2 = 4 \times 10^{-4}$. The number of particles is $L = 1000$ and exponential weight $r = 10$. This parameter setup is found adequate for all following experiments.

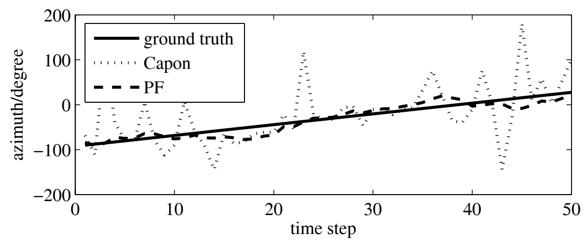
Figure 2 presents the DOA estimation by using Capon beamforming and proposed PF tracking approach under different experiment environments: 1) SNR $= -10$dB, $N = 1024$; and 2) SNR $= -6$dB, $N = 32$. Capon beamforming degrades sharply when the SNR is low and the number of snapshots is small: at a number of time steps, the DOA estimates are far from the ground truth. However, PF is able to incorporate the temporal information (from the source dynamic model) as well as the spatial information (from the current measurements), and is thus able locate the source consistently. It always locks on to the source and presents a satisfactory DOA estimation. In addition, although the initial DOA is unknown for PF and is assumed to be uniformly distributed, the PF tracking approach is able to converge to the ground truth very quickly.



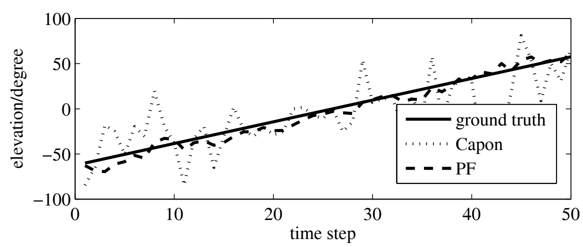
(a)



(b)



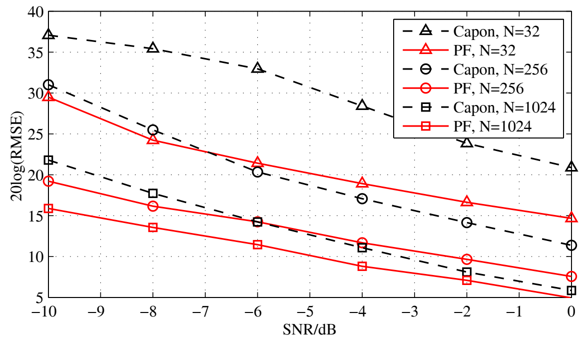
(c)



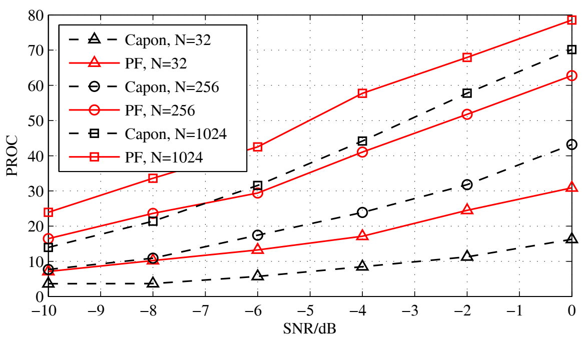
(d)

Figure 2: 2-D DOA estimation under different experiment environments. (a) azimuth estimation and (b) elevation estimation under SNR $= -10$dB, $N = 1024$; (c) azimuth estimation and (d) elevation estimation under SNR $= -6$dB, $N = 32$.

To fully evaluate the tracking performance, experiments under different number of snapshots and different simulated noisy environments (different SNRs) are organized. The root mean square error (RMSE) and the probability of correct estimate (PROC) over 50 Monte Carlo simulations are used to evaluate the DOA estimation performance. An estimate is regarded as a correct estimate if the absolute error is less than 2°, and PROC is defined as the percentage of correct estimates. Fig. 3(a) and (b) present the RMSE and PROC versus different SNR under different number of snapshots respectively. Different SNRs from -10dB to 0dB with an increment of 2dB are employed to generate noisy environments. The number of snapshots used here are $N = [32, 256, 1024]$. Due to incorporating the temporal



(a)



(b)

Figure 3: (a) RMSE in dB and (b) PROC in percentage *vs.* different SNR and different number of snapshots.

information, the proposed PF tracking algorithm performs better than Capon localization method in estimating the DOA, and fewer snapshots are needed to achieve a similar accuracy. A remarkable advantage of the PF tracking algorithm is its ability to alleviate the effect of noise and keep locking on the source DOA, even in a very low SNR environment (e.g., SNR $= -10$dB). In the scenarios where limited snapshots are available (e.g., $N = 32$), the RMSE can be significantly reduced by using the proposed PF tracking approach.

It is worth mentioning that the proposed PF algorithm is also suitable for real-time online implementation. The computation complexity is obviously reduced compared to the DOA estimation using Capon beamforming. In the above experiments, the 2-D DOA space is split into 100×100 grids to implement the 2-D search of Capon beamforming (14). The calculation of the Capon response is thus 1.0×10^4 times. However, if 1000 particles are used in PF tracking algorithm, it is only necessary to calculate the likelihood function 1.0×10^3 times. Besides, there is no matrix inverse operation in the likelihood evaluation as required in Capon response calculation.

5. CONCLUSIONS

A new approach for 2-D DOA tracking of an acoustic source using a single AVS is presented. A CV model is employed to model the source dynamics and the AVS data based likelihood model is developed to weight the particles. The likelihood is further exponentially weighted to enhance the weight of particles at high likelihood area. By incorporating both the temporal and spatial information, the proposed PF tracking algorithm significantly outperforms the traditional Capon beamforming method in 2-D DOA estimation, and is also able to achieve better accuracy in the adverse environments with fewer snapshots. However, only a single acoustic source and a single AVS is considered in this paper. Hence, future work includes developing a PF algorithm to track multiple acoustic source using a single AVS as well as an AVS array.

REFERENCES

[1] H. Krim and M. Viberg, “Two decades of array signal processing research: the parametric approach,” *IEEE Signal Process. Mag.*, vol. 13, no. 4, pp. 67–94, 1996.

[2] A. Nehorai and E. Paldi, “Acoustic vector-sensor array processing,” *IEEE Trans. Signal Process.*, vol. 42, no. 9, pp. 2481–2491, 1994.

[3] M. Hawkes and A. Nehorai, “Acoustic vector-sensor beamforming and capon direction estimation,” *IEEE Trans. Signal Process.*, vol. 46, no. 9, pp. 2291–2304, 1998.

[4] P. Tichavsky, K. T. Wong, and M. D. Zoltowski, “Near-field/far-field azimuth and elevation angle estimation using a single vector hydrophone,” *IEEE Trans. Signal Process.*, vol. 49, no. 11, pp. 2498–2510, 2001.

[5] P. K. Tam and K. T. Wong, “Cramér-rao bounds for direction finding by an acoustic vector sensor under nonideal gain-phase responses, noncollocation, or nonorthogonal orientation,” *IEEE Sensors J.*, vol. 9, no. 8, pp. 969–982, 2009.

[6] K. T. Wong and M. D. Zoltowski, “Self-initiating MUSIC-based direction finding in underwater acoustic particle velocity-field beamspace,” *IEEE J. Ocean. Eng.*, vol. 25, no. 2, pp. 262–273, 2000.

[7] M. Arulampalam, S. Maskell, N. Gordon, and T. Clapp, “A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking,” *IEEE Trans. Signal Process.*, vol. 50, no. 2, pp. 174–188, Feb. 2002.

[8] J. V. Candy, “Bootstrap particle filtering,” *IEEE Signal Process. Mag.*, vol. 24, no. 54, pp. 73–85, Jul. 2007.

[9] C. Yardim, P. Gerstoft, and W. S. Hodgkiss, “Geoacoustic and source tracking using particle filtering: experimental results,” *J. Acoust. Soc. Amer.*, vol. 128, no. 1, pp. 75–87, Jul. 2010.

[10] X. Rong Li and V. P. Jilkov, “Survey of maneuvering target tracking. part 1: Dynamic models,” *IEEE Trans. Aerosp. Electron. Syst.*, vol. 39, no. 4, pp. 1333–1364, Oct. 2003.