MEFPDA-SCKF for underwater single observer bearings-only target tracking in clutter

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Abstract—The **MEFPDA-SCKF algorithm, which is based on square-root cubature Kalman filter (SCKF) and maximum entropy fuzzy probabilistic data association (MEFPDA), is proposed for single observer bearings-only target tracking in cluttered underwater environment. SCKF is used to solve the nonlinear state estimation of bearings-only tracking. MEFPDA is used to reduce the interference of clutter and provide reliable bearings. Simulation and field experiment are conducted to verify the effectiveness of the proposed algorithm.**

Keywords—Bearings-only tracking; square-root cubature Kalman filter (SCKF); probabilistic data association (PDA); maximum entropy fuzzy probabilistic data association (MEFPDA)

I. INTRODUCTION

At present, more and more scientists are fascinated with the mysterious ocean. Using bearings-only tracking method, the observer can track the target without the risk of being detected [1]. So bearings-only tracking is becoming a hot topic in ocean application areas. Typical applications including both scientific researches and safety activities are marine mammals tracking, homeland security, underwater anti-terrorism and so on [2-3].

However, single observer bearings-only target tracking has low accuracy and diverges easily because of weak observability and nonlinearity in essentially; moreover, the underwater clutter will deteriorate the tracking performance. So it is necessary for us to do some deep research to improve the accuracy of underwater single observer bearings-only target tracking in cluttered environment.

As the bearings-only target tracking is a nonlinear system in essentially, some nonlinear methods have been applied to it. The extended Kalman filter (EKF) [4] is an early nonlinear filter, and has been used in bearings-only tracking, but it has some flaws such as low accuracy, instability and divergence. The unscented Kalman filter (UKF) [5] based on Unscented Transform (UT) is another nonlinear filter that has been applied to bearings-only tracking, it has better accuracy than EKF, however, its accuracy will decrease when the state dimensionality is relatively high, moreover, the appearance of negative definite covariance matrix will lead to computational problems. To overcome the shortcomings of traditional nonlinear filters, the square-root cubature Kalman filter (SCKF) [6] has been proposed. SCKF improves the accuracy and stability for nonlinear state estimation and even has good performance for high dimensional state estimation [7-8].

However, the interference of clutter was ignored in most nonlinear filter methods, and consequently these methods can't be applied to engineering. So the data association method, which is used to select the true measurement, is vital for bearings-only target tracking in cluttered underwater environment. Probabilistic data association (PDA) [9] is a very classical and effective data association method. PDA associates all measurements in the validation region to the target probabilistically. The maximum entropy fuzzy probabilistic data association (MEFPDA) [10] is proposed in literature. It introduces a new weight assignment method to deal with the uncertainty of the measurements, and it has better performance while with lower computation load.

Taking full advantage of SCKF and MEFPDA, a novel MEFPDA-SCKF algorithm is proposed in this paper for underwater single observer bearings-only target tracking in clutter.

II. PROBLEM FORMULATION

The intent of bearings-only tracking is to estimate the kinematics, such as the position and velocity of the target, utilizing bearing data only [11-12]. The position and velocity vector of the target is defined as (x^t, y^t), $(\dot{x}^t, \dot{y}^t)$ respectively, and the state vector of the target is defined as

$$\boldsymbol{x}^t = [x^t, \dot{x}^t, y^t, \dot{y}^t] \tag{1}$$

similarly, the state vector of the observer is defined as

$$\boldsymbol{x}^o = [x^o, \dot{x}^o, y^o, \dot{y}^o] \tag{2}$$

and the system state vector is defined as

$$\boldsymbol{x} = \boldsymbol{x}^t - \boldsymbol{x}^o = [x, \dot{x}, y, \dot{y}] \tag{3}$$

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We assume that the velocity of target is nearly constant, so the discrete time dynamics model is given as

$$\boldsymbol{x}_{k+1} = \boldsymbol{F}\boldsymbol{x}_k + \boldsymbol{U}_{k,k+1} + \boldsymbol{G}\boldsymbol{w}_k \tag{4}$$

where

$$\boldsymbol{F} = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{5}$$

$$\boldsymbol{U}_{k,k+1} = \begin{bmatrix} x_k^o + T\dot{x}_k^o - x_{k+1}^o \\ \dot{x}_k^o - \dot{x}_{k+1}^o \\ y_k^o + T\dot{y}_k^o - y_{k+1}^o \\ \dot{y}_k^o - \dot{y}_{k+1}^o \end{bmatrix} \tag{6}$$

$$\boldsymbol{G} = \begin{bmatrix} T^2/2 & 0 \\ T & 0 \\ 0 & T^2/2 \\ 0 & T \end{bmatrix} \tag{7}$$

$\boldsymbol{F}$ is the state transition matrix, and T is the sampling interval. $\boldsymbol{w}_k$ is a 2-by-1 independent and identically distributed process noise vector with the distribution $\boldsymbol{w}_k \sim N(0,\boldsymbol{Q})$,where $\boldsymbol{Q} = diag\left[\sigma_a^2 \quad \sigma_a^2\right]$

The measurement equation for single observer bearings-only target tracking is given as

$$z_k = h(\boldsymbol{x}_k) + v_k = \arctan\left(\frac{x_k}{y_k}\right) + v_k \tag{8}$$

where z_k is the bearing measurement, and v_k is the measurement noise with the distribution $v_k \sim N(0,\sigma_\theta^2)$

III. MEFPDA-SCKF ALGORITHM

A. SCKF Algorithm

The SCKF is a square-root version of the cubature Kalman filter (CKF), it avoids square-rooting operations of the CKF by propagating the square-root factor of error covariance directly. $\boldsymbol{S} = Tria(\boldsymbol{A})$ represents the QR decomposition, which is used in the SCKF to compute the square-root factor indirectly.

The complete specification of the SCKF is given as follows.

1) Initialization.

$$\hat{\boldsymbol{x}}_0 = \mathrm{E}[\boldsymbol{x}_0] \quad \boldsymbol{S}_0 = \mathrm{chol}(\mathrm{E}[(\boldsymbol{x}_0 - \hat{\boldsymbol{x}}_0)(\boldsymbol{x}_0 - \hat{\boldsymbol{x}}_0)^{\mathrm{T}}]) \tag{9}$$

where $\boldsymbol{S}_0$ is a lower triangular matrix.

For $k \in \{1,2,...,\infty\}$

2) Time update.
Calculate the cubature points ($i = 1,...,m$)

$$\boldsymbol{X}_{i,k-1} = \boldsymbol{S}_{k-1}\xi_i + \hat{\boldsymbol{x}}_{k-1} \tag{10}$$

where $m = 2n$, n is the state dimensionality. $\boldsymbol{\xi}_i$ is the i th column of matrix $\sqrt{n} * [\boldsymbol{I}_{n\times n}, -\boldsymbol{I}_{n\times n}]$, $\boldsymbol{I}_{n\times n}$ represents the identity matrix of dimension n .

Calculate the propagated cubature points according to the process equation($i = 1,2,...,m$)

$$\boldsymbol{X}^*_{i,k|k-1} = f(\boldsymbol{X}_{i,k-1}, \boldsymbol{u}_{k-1}) \tag{11}$$

Estimate the predicted state

$$\hat{\boldsymbol{x}}_{k|k-1} = \frac{1}{m}\sum_{i=1}^{m} \boldsymbol{X}^*_{i,k|k-1} \tag{12}$$

Calculate the square-root factor of the predicted error covariance

$$\boldsymbol{S}_{k|k-1} = \mathrm{Tria}\left(\left[\tilde{\boldsymbol{X}}^*_{k|k-1} \quad \boldsymbol{S}_{Q,k-1}\right]\right) \tag{13}$$

where $\boldsymbol{S}_{Q,k-1}$ represents a square-root factor of the process noise covariance $\boldsymbol{Q}_{k-1}$ and

$$\tilde{\boldsymbol{X}}^*_{k|k-1} = \frac{1}{\sqrt{m}}\left[\boldsymbol{X}^*_{1,k|k-1} - \hat{\boldsymbol{x}}_{k|k-1} \ldots \boldsymbol{X}^*_{m,k|k-1} - \hat{\boldsymbol{x}}_{k|k-1}\right] \tag{14}$$

3) Measurement update.
Evaluate the cubature points ($i = 1,...,m$)

$$\boldsymbol{X}_{i,k|k-1} = \boldsymbol{S}_{k|k-1}\xi_i + \hat{\boldsymbol{x}}_{k|k-1} \tag{15}$$

Compute the propagated cubature points according to the measurement equation ($i = 1,\ldots,m$)

$$\boldsymbol{Z}_{i,k|k-1} = h(\boldsymbol{X}_{i,k|k-1}) \tag{16}$$

Estimate the predicted measurement

$$\hat{z}_{k|k-1} = \frac{1}{m}\sum_{i=1}^{m} \boldsymbol{Z}_{i,k|k-1} \tag{17}$$

Compute the square-root factor of the measurement predicted error covariance matrix

$$\boldsymbol{S}_{zz,k|k-1} = \mathrm{Tria}\left(\left[\tilde{\boldsymbol{Z}}_{k|k-1} \quad \boldsymbol{S}_{R,k}\right]\right) \tag{18}$$

where $\boldsymbol{S}_{R,k}$ represents the square-root factor of the measurement noise covariance $\boldsymbol{R}_k$ and

$$\tilde{\boldsymbol{Z}}_{k|k-1} = \frac{1}{\sqrt{m}}\left[\boldsymbol{Z}_{1,k|k-1} - \hat{\boldsymbol{z}}_{k|k-1} \cdots \boldsymbol{Z}_{m,k|k-1} - \hat{\boldsymbol{z}}_{k|k-1}\right] \quad (19)$$

Calculate the cross-covariance matrix

$$\boldsymbol{P}_{xz,k|k-1} = \tilde{\boldsymbol{X}}_{k|k-1}\tilde{\boldsymbol{Z}}_{k|k-1}^{\mathrm{T}} \quad (20)$$

where

$$\tilde{\boldsymbol{X}}_{k|k-1} = \frac{1}{\sqrt{m}}\left[\boldsymbol{X}_{1,k|k-1} - \hat{\boldsymbol{x}}_{k|k-1} \cdots \boldsymbol{X}_{m,k|k-1} - \hat{\boldsymbol{x}}_{k|k-1}\right] \quad (21)$$

Calculate the Kalman gain matrix

$$\boldsymbol{K}_k = \left[\boldsymbol{P}_{xz,k|k-1} / \boldsymbol{S}_{zz,k|k-1}^{T}\right] / \boldsymbol{S}_{zz,k|k-1} \quad (22)$$

Update the state

$$\hat{\boldsymbol{x}}_k = \hat{\boldsymbol{x}}_{k|k-1} + \boldsymbol{K}_k(\boldsymbol{z}_k - \hat{\boldsymbol{z}}_{k|k-1}) \quad (23)$$

Calculate the square-root factor of the corresponding error covariance

$$\boldsymbol{S}_k = \mathrm{Tria}\left(\left[\tilde{\boldsymbol{X}}_{k|k-1} - \boldsymbol{K}_k\tilde{\boldsymbol{Z}}_{k|k-1} \quad \boldsymbol{K}_k\boldsymbol{S}_{R,k}\right]\right) \quad (24)$$

B. PDA-SCKF Algorithm

First of all, we compute from (9)-(22) as in SCKF algorithm.

The elliptical validation region designed to select possible measurements is denoted as

$$D_{k,\gamma} = \left\{\boldsymbol{z} : \left[\boldsymbol{z} - \hat{\boldsymbol{z}}_{k|k-1}\right]^{\mathrm{T}}\left(\boldsymbol{S}_{zz,k|k-1}\boldsymbol{S}_{zz,k|k-1}^{\mathrm{T}}\right)^{-1}\left[\boldsymbol{z} - \hat{\boldsymbol{z}}_{k|k-1}\right] \le \gamma\right\} \quad (25)$$

where $\boldsymbol{S}_{zz,k|k-1}$ is the square-root factor of the measurement predicted error covariance matrix, computed by (18), and γ is the threshold.

The set of validated measurements at time k is denoted as

$$Z_k = \left\{\boldsymbol{z}_{i,k}\right\}_{i=1}^{m(k)} \quad (26)$$

where $\boldsymbol{z}_{i,k}$ represents the i th validated measurement and $m(k)$ is the number of validated measurements.

Under the assumption that the i th measurement originate from the target, the state can be updated as

$$\hat{\boldsymbol{x}}_{i,k} = \hat{\boldsymbol{x}}_{k|k-1} + \boldsymbol{K}_k\boldsymbol{v}_{i,k} \quad i = 1,\ldots,m(k) \quad (27)$$

where $\boldsymbol{v}_{i,k}$ is the innovation corresponding with the i th measurement.

Under the assumption that none of the measurements originates from the target, the state can be updated as

$$\hat{\boldsymbol{x}}_{0,k} = \hat{\boldsymbol{x}}_{k|k-1} \quad (28)$$

According to the assumptions above, and the state at time k can be updated as

$$\begin{aligned}\hat{\boldsymbol{x}}_k &= \sum_{i=0}^{m(k)} \hat{\boldsymbol{x}}_{i,k}\beta_{i,k} \\ &= \hat{\boldsymbol{x}}_{k|k-1} + \boldsymbol{K}_k\boldsymbol{v}_k\end{aligned} \quad (29)$$

where $\beta_{i,k}$ ($i = 1,\cdots,m(k)$) is the probability that the i th measurement originates from the target, $\beta_{0,k}$ is the probability that none of the measurements originates from the target or there is no validated measurement, and $\boldsymbol{v}_k$ is the combined innovation denoted as

$$\boldsymbol{v}_k = \sum_{i=1}^{m(k)} \beta_{i,k}\boldsymbol{v}_{i,k} \quad (30)$$

The covariance corresponding with the updated state is

$$\begin{aligned}\boldsymbol{P}_k = \boldsymbol{P}_{k|k-1} &- (1-\beta_{0,k})\boldsymbol{K}_k\left(\boldsymbol{S}_{zz,k|k-1}\boldsymbol{S}_{zz,k|k-1}^{\mathrm{T}}\right)\boldsymbol{K}_k^{\mathrm{T}} \\ &+ \boldsymbol{K}_k\left[\sum_{i=1}^{m(k)} \beta_{i,k}\boldsymbol{v}_{i,k}\boldsymbol{v}_{i,k}^{\mathrm{T}} - \boldsymbol{v}_k\boldsymbol{v}_k^{\mathrm{T}}\right]\boldsymbol{K}_k^{\mathrm{T}}\end{aligned} \quad (31)$$

where $\boldsymbol{S}_{zz,k|k-1}$ is the square-root factor of innovation covariance matrix, computed by (18). Using the fact that $\boldsymbol{P}_{k|k-1} = \tilde{\boldsymbol{X}}_{k|k-1}\tilde{\boldsymbol{X}}_{k|k-1}^{\mathrm{T}}$ and some manipulations in (31) lead to

$$\boldsymbol{P}_k = \tilde{\boldsymbol{X}}_{k|k-1}\tilde{\boldsymbol{X}}_{k|k-1}^{\mathrm{T}} + \boldsymbol{K}_k\boldsymbol{P}_k^{E}\boldsymbol{K}_k^{\mathrm{T}} \quad (32)$$

where

$$\boldsymbol{P}_k^{E} = \sum\nolimits_{i=1}^{m(k)} \beta_{i,k}\boldsymbol{v}_{i,k}\boldsymbol{v}_{i,k}^{\mathrm{T}} - \boldsymbol{v}_k\boldsymbol{v}_k^{\mathrm{T}} - (1-\beta_{0,k})\boldsymbol{S}_{zz,k|k-1}\boldsymbol{S}_{zz,k|k-1}^{\mathrm{T}} \quad (33)$$

Factorize

$$P_k^{E} = \boldsymbol{S}_{e,k}\boldsymbol{S}_{e,k}^{\mathrm{T}} \quad (34)$$

Then, the square-root factor of the covariance corresponding with the updated state can be written as

$$\boldsymbol{S}_k = \mathrm{Tria}\left(\left[\tilde{\boldsymbol{X}}_{k|k-1} \quad \boldsymbol{K}_k\boldsymbol{S}_{e,k}\right]\right) \quad (35)$$

Concerning the association probability $\beta_{i,k}$, it is calculated as following (36), using the nonparametric PDA method described in [13].

$$\beta_{i,k} = \begin{cases} \dfrac{e_i}{b + \sum_{j=1}^{m(k)} e_j}, i = 1, \dots, m(k) \\ \dfrac{b}{b + \sum_{j=1}^{m(k)} e_j}, i = 0 \end{cases} \tag{36}$$

where

$$e_i = \exp\left[-\frac{1}{2} v_{i,k}^{\mathrm{T}} \boldsymbol{S}_{zz,k|k-1} \boldsymbol{S}_{zz,k|k-1}^{\mathrm{T}} v_{i,k} \right] \tag{37}$$

$$b = \left(\frac{2\pi}{\gamma} \right)^{\frac{M}{2}} m(k) C_M^{-1} \frac{1 - P_D P_G}{P_D} \tag{38}$$

where P_{D} is detection probability, and P_{G} is gate probability.

C. MEFPDA-SCKF Algorithm

The MEFPDA-SCKF has the same structure as PDA-SCKF, the only difference is that the association probability is computed in a different way, which is described as following.

As in PDA-SCKF, we suppose that $m(k)$ measurements are validated at time k and the set of them is denoted as (26).

For the calculation of association probability, there are two situations to be discussed.

1) No validated measurement

If there is no validated measurement, i.e., $m(k) = 0$, the association probability (just $\beta_{0,k}$) is denoted as

$$\beta_{0,k} = 1 \tag{39}$$

2) At least one validated measurement

If there is at least one validated measurement, i.e., $m(k) > 0$, the data association problem is regarded as the clustering process, and the maximum entropy fuzzy clustering principle is used to compute the association probability. The objective function to be maximized by the Lagrange multiplier method, whose detailed derivation can be found in [10], is defined as

$$J(U,C) = -\sum_{i=1}^{m(k)} u_i \mathrm{In} u_i - \alpha \sum_{i=1}^{m(k)} u_i d\left(\boldsymbol{z}_{i,k}, c \right) + \lambda \left(\sum_{i=1}^{m(k)} u_i - 1 \right) \tag{40}$$

where u_i is the fuzzy membership degree, $d(\boldsymbol{z}_{i,k}, c)$ is the Mahalanobis distance between the measurement $\boldsymbol{z}_{i,k}$ and the cluster center, α and λ are the Lagrange multipliers.

By maximizing (40), u_i is derived as

$$u_i = \frac{\exp\left[-\alpha d\left(\boldsymbol{z}_{i,k}, c \right) \right]}{\sum_{j=1}^{m(k)} \exp\left[-\alpha d\left(\boldsymbol{z}_{j,k}, c \right) \right]} \tag{41}$$

and in MEFPDA-SCKF, u_i is viewed as the association probability, i.e.

$$\beta_{i,k} = \begin{cases} 0 & i = 0 \\ u_i & i = 1, \dots, m(k) \end{cases} \tag{42}$$

IV. EXPERIMENTS

In this section, simulation and field experiment are conducted to show the effectiveness of the proposed algorithm.

A. Simulation

The MEFPDA-SCKF algorithm is compared against PDA-SCKF in this simulation. For a fair comparison, 50 Monte Carlo runs are performed. The parameters used in simulation is shown in Table 1. The simulation scenario and estimated trajectory of target are shown in Fig. 1. The RMS position and velocity error are shown in Figs. 2 and 3, respectively. From the two figures, it can be seen that the RMS error of MEFPDA-SCKF is smaller than that of PDA-SCKF.

The comparison of running time, which reflects the computation load, is shown in Table 2. It shows that the computation load of MEFPDA-SCKF is a litter lower than that of PDA-SCKF.

TABLE 1. PARAMETERS USED IN TRACKING SCENARIO

Target initial position	(0 m,-3000 m)
Target velocity	5 m/s
Target course	315°
Observer initial position	(0 m,0 m)
Observer velocity	3 m/s
Observer course (0-400s)	300°
Observer course (400-900s)	285°
Detection probability	0.9
Sampling interval	0.5 s

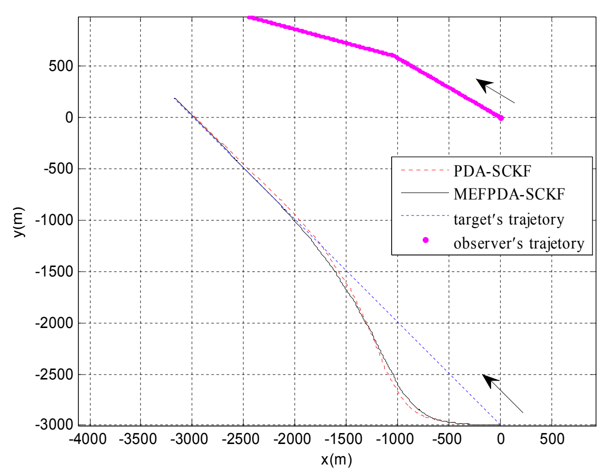

Fig. 1. Simulation scenario and target's trajectory estimation.

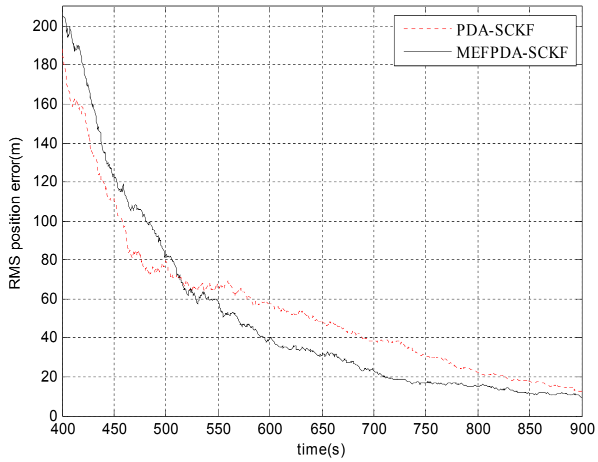

Fig. 2. RMS position error.

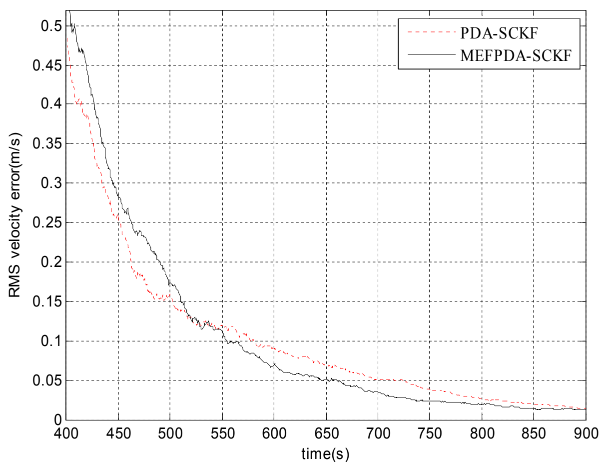

Fig. 3. RMS velocity error.

TABLE 2. COMPARISON OF THE RUNNING TIME

	PDA-SCKF	***MEFPDA-SCKF***
50 Monte Carlo runs (s)	25.5530	25.1006
Single run (ms)	511	502
Single-step (ms)	0.2839	0.2789

B. Field experiment

The field experiment is conducted to show the effectiveness of the proposed algorithm. The trajectory of the target and observer are shown in Fig. 4, the initial position of the target and observer are $(-1486\text{m}, 1697\text{m})$ and $(0\text{m}, 0\text{m})$, respectively.

Some parameters of the tracking system are as follows:

$$\hat{\boldsymbol{x}}_0 = [\text{-}1500 \quad 0 \quad 1700 \quad 0]^{\mathrm{T}}$$

$$\boldsymbol{P}_0 = \mathrm{diag}[900 \quad 0.25 \quad 900 \quad 0.25] \;\; \boldsymbol{s}_0 = \mathrm{chol}(\boldsymbol{P}_0)$$

$$\boldsymbol{Q} = \mathrm{diag}[0.000006 \quad 0.000006] \quad \sigma_\theta = 2\pi/180$$

The measured bearings, which is corrupted by noise and clutter, is shown in Fig. 5. The MEFPDA-SCKF is applied to single observer bearings-only target tracking, and its performance is compared against that of PDA-SCKF. The position and velocity estimation error are shown in Figs. 6 and 7, respectively. The comparison of running time, which reflects the computation load, is shown in Table 3.

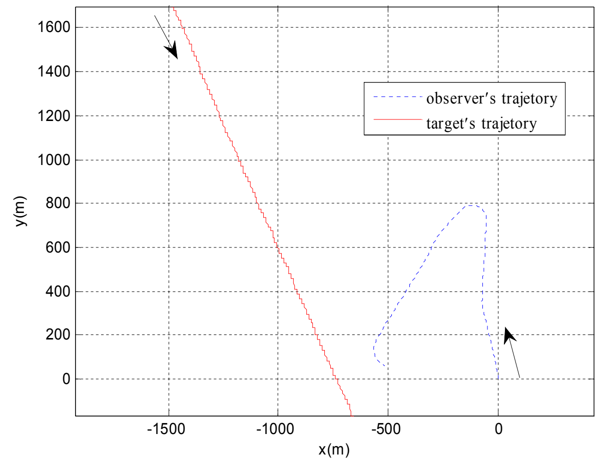

Fig. 4. Trajectory of the observer and target.

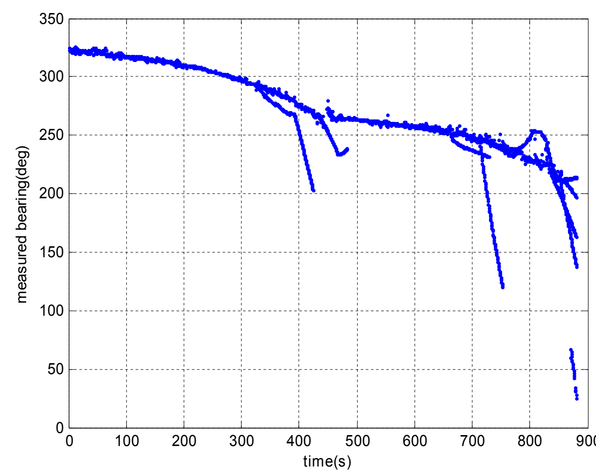

Fig. 5. The measured bearings.

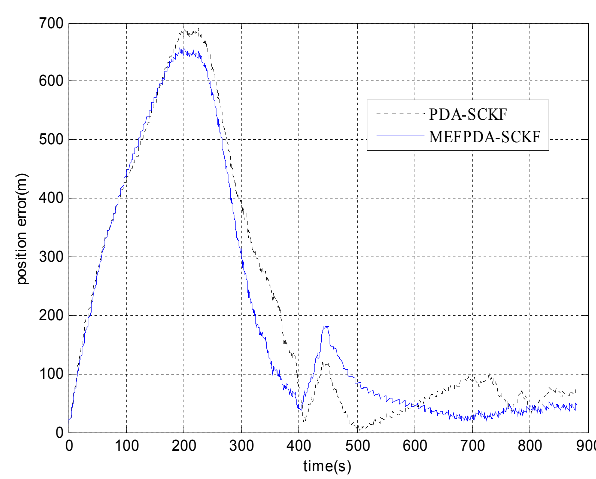

Fig. 6. Position estimation error.

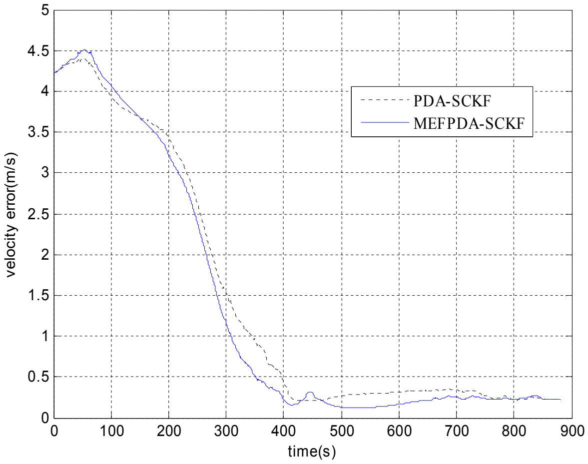

Fig. 7. Velocity estimation error.

TABLE 3. COMPARISON OF RUNNING TIME

	PDA-SCKF	***MEFPDA-SCKF***
Total(s)	0.4212	0.4056
Single-step(ms)	0.2393	0.2305

From Figs. 6 and 7, we can see that the tracking accuracy of MEFPDA-SCKF is higher than that of PDA-SCKF. From Table 3, it can be seen that the computation load of MEFPDA-SCKF is a litter lower than that of PDA-SCKF.

V. CONCLUSION

MEFPDA-SCKF is proposed in this paper for the problem of single observer bearings-only target tracking in cluttered underwater environment. Simulation and field experiment show that MEFPDA-SCKF is better than PDA-SCKF in terms of accuracy and computation load. The good performance of the proposed algorithm stems from the new weight assignment, which is introduced from a modified version of maximum entropy fuzzy clustering. The detection probability, which is difficult to get in engineering, is required in PDA-SCKF. However, the detection probability is not required in MEFPDA-SCKF. So, MEFPDA-SCKF is easier to implement than PDA-SCKF in engineering.

Time delay of signal and the maneuver of the target are not considered in this paper, in the future, we will consider these two problems.

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