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Federated UKF algorithm for mobile location estimation with TDOA/Doppler measurements

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Abstract: In order to enhance the location estimation performance of mobile station(MS) tracking and positioning, a new method of mobile location optimal estimation based on the federated filtering structure and the simplified unscented Kalman filter (UKF) is presented. The proposed algorithm uses the Singer mobile statement model as the reference system, and the simplified UKF as the subfilters. The subfilters receive the two groups of independently detected time difference of arrival (TDOA) measurement inputs and Doppler measurement inputs, and produce local estimation outputs to the main estimator. Then the main estimator performs the optimal fusion of the local estimation outputs according to the scalar weighted rule, and a global optimal or suboptimal estimation result is achieved. Finally the main estimator gives feedback and reset information to the subfilters and the reference system for next step estimation. In the simulations, the estimation performance of the proposed algorithm is evaluated and compared with the simplified UKF method with TDOA or Doppler measurement alone. The simulation results demonstrate that the proposed algorithm can effectively reduce the location estimation error and variance of the MS, and has favorable performance in both root mean square error(RMSE) and mean error cumulative distribution function(CDF).

Key words: data fusion; mobile location estimation; federated filtering; unscented Kalman filter(UKF)

Mobile location estimation involves locating the position of a mobile station(MS) based on the measured radio signals from its neighborhood base stations (BSs) in wireless communications networks, such as radar, multi-sensor, cellular and digital broadcasting systems. Mobile location estimation has attracted considerable interest in recent researches. There are a number of possible applications for mobile location estimation, including Emergency-911[1], fleet management, navigation systems, and other location-based services(LBSs).

Typical measuring techniques for locating a mobile station in two dimensions can be categorized into received signal strength(RSS), time of arrival(TOA), time difference of arrival(TDOA)[2], and the angle of arrival(AOA). With the development of modern signal processing techniques, Doppler measurements in the received signals are employed and proved to enhance the performance of maneuvering tracking and positioning[3-4].

In order to better estimate a mobile's location, data fusion filtering approaches with multiple measurements are often investigated and used in reality systems. There are two representative data fusion methods. One is the JDL model based fusion architecture presented in Ref. [5], which needs four levels of fusion with TOA/TDOA data and the Taylor series method and fits mainly for a stationary positioning case; the other is the Kalman filtering(KF) based data fusion, including measurement fusion and statement fusion[6-7]. The statement fusion method can be further divided into concentrated fusion and distributed fusion. Among the various KF data fusion methods, the federated KF filter proposed by Carlson[8] is the most widely recognized. As one kind of distributed measurement fusion method, it carries lower computation complexity than the concentrated measurement fusion approach, and has favorable performances in design flexibility and fault tolerance.

In this paper, a federated filter method with TDOA/Doppler measurements based on the simplified unscented Kalman filter(UKF) is proposed. As illustrated in Fig. 1, the mobile statement model works as the reference system. The simplified UKF subfilters receive the measurements directly from the sensors, and provide the state estimate and error covariance information to the main estimator for recombination. Then the main estimator performs optimal fusion and outputs a global optimal or nearly global optimal estimation. Finally, the main estimator gives feedback and reset information to the subfilters and the reference system.

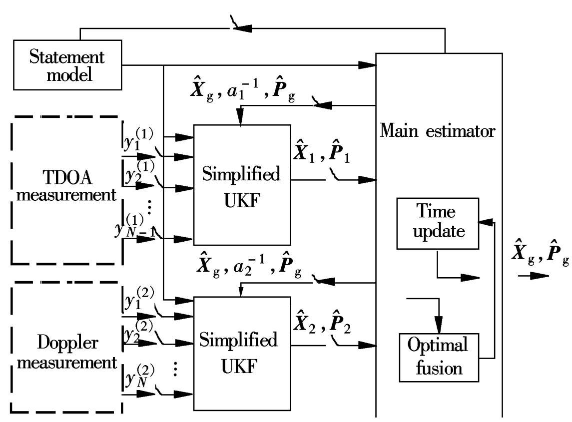

Fig. 1 The proposed federated filter algorithm

1 System Description

1.1 Mobile state model

The Singer model[9] is chosen as the movement statement model of the MS. Let the state of the MS at time instant k be defined as the vector $\boldsymbol{x}_k = \{x_k, \dot{x}_k, \ddot{x}_k, y_k, \dot{y}_k, \ddot{y}_k\}^{\mathrm{T}}$. The state formulations are as follows:

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$$\boldsymbol{x}_k = f(\boldsymbol{x}_{k-1}, k-1) + \boldsymbol{q}_{k-1} = \boldsymbol{F}_{k-1}\boldsymbol{x}_{k-1} + \boldsymbol{q}_{k-1} \quad (1)$$

$$\boldsymbol{F}_{k-1} = \mathrm{diag}(\boldsymbol{A}_x, \boldsymbol{A}_y), \boldsymbol{A}_x = \boldsymbol{A}_y = \begin{bmatrix} 1 & T & \alpha^{-2}(\mathrm{e}^{-\alpha T} - 1 + \alpha T) \\ 0 & 1 & \alpha^{-1}(1 - \mathrm{e}^{-\alpha T}) \\ 0 & 0 & \mathrm{e}^{-\alpha T} \end{bmatrix} \quad (2)$$

$$\boldsymbol{Q}_{k-1} = \mathrm{diag}(\boldsymbol{Q}_x, \boldsymbol{Q}_y),\ \boldsymbol{Q}_x = \boldsymbol{Q}_y = 2\alpha\sigma_{\mathrm{m}}^2 \begin{bmatrix} q_{11} & q_{12} & q_{13} \\ q_{21} & q_{22} & q_{23} \\ q_{31} & q_{32} & q_{33} \end{bmatrix} \quad (3)$$

where T is the sampling period; α is the reciprocal of the acceleration time constant; σ_{m}^2 is the variance of MS acceleration; $\boldsymbol{q}_{k-1} \sim N(0, \boldsymbol{Q}_{k-1})$ is the additive white Gaussian process noise at the $(k-1)$-th step with covariance matrix $\boldsymbol{Q}_{k-1}$. The values of q_{ij}, $i, j = 1, 2, 3$ can be found in Ref. [9].

1.2 Measurement models

Let $\boldsymbol{y}_k^{(1)} = \{y_{1,k}^{(1)}, y_{2,k}^{(1)}, \ldots, y_{N-1,k}^{(1)}\}^{\mathrm{T}}$ be the range difference observation vector by the TDOA method at time instant k. The TDOA measurement equations can be expressed as

$$\boldsymbol{y}_k^{(1)} = \boldsymbol{H}_1(\boldsymbol{x}_k, k) + \boldsymbol{v}_1(k) \quad (4)$$

$$\boldsymbol{H}_1(\boldsymbol{x}_k, k) = \{r_{2,1}(k), r_{3,1}(k), \ldots, r_{N,1}(k)\}^{\mathrm{T}} \quad (5)$$

$$r_{i,1}(k) = \sqrt{(x_{\mathrm{B}i} - x_{1,k})^2 + (y_{\mathrm{B}i} - x_{4,k})^2} - \sqrt{(x_{\mathrm{B}1} - x_{1,k})^2 + (y_{\mathrm{B}1} - x_{4,k})^2} \quad i = 2, 3, \ldots, N \quad (6)$$

where $(x_{\mathrm{B}i}, y_{\mathrm{B}i})$, $i = 1, 2, \ldots, N$ indicates the position of the i-th BS; N is the number of the BSs; $r_{i,1}(k)$ is the difference between the range from MS to the i-th BS and the range from MS to the first BS at step k. $v_1(k) \sim N(0, R_1(k))$ is the TDOA additive measurement noise at step k.

Let $\boldsymbol{y}_k^{(2)} = \{y_{1,k}^{(2)}, y_{2,k}^{(2)}, \ldots, y_{N,k}^{(2)}\}^{\mathrm{T}}$ be the radical velocity observation vector in the Doppler method at time instant k. The Doppler measurement equations can be written as

$$\boldsymbol{y}_k^{(2)} = \boldsymbol{H}_2(\boldsymbol{x}_k, k) + \boldsymbol{v}_2(k) \quad (7)$$

$$\boldsymbol{H}_2(\boldsymbol{x}_k, k) = \{v_{r,1}(k), v_{r,2}(k), \ldots, v_{r,N}(k)\}^{\mathrm{T}} \quad (8)$$

$$v_{r,i}(k) = \frac{(x_{1,k} - x_{\mathrm{B}i})x_{2,k} + (x_{4,k} - y_{\mathrm{B}i})x_{5,k}}{\sqrt{(x_{\mathrm{B}i} - x_{1,k})^2 + (y_{\mathrm{B}i} - x_{4,k})^2}} \quad i = 1, 2, \ldots, N \quad (9)$$

where $\boldsymbol{v}_2(k) \sim N(0, \boldsymbol{R}_2(k))$ is the Doppler additive measurement noise at step k.

1.3 Problem statement

Based on the discussions above, the overall dynamic model of the system can be depicted as

$$\left.\begin{aligned} \boldsymbol{x}_k &= f(\boldsymbol{x}_{k-1}, k-1) + \boldsymbol{q}_{k-1} \\ \boldsymbol{y}_k^{(j)} &= \boldsymbol{H}_j(\boldsymbol{x}_k, k) + \boldsymbol{v}_j(k) \qquad j = 1, 2 \end{aligned}\right\} \quad (10)$$

Here the two groups of TDOA/Doppler measurements are supposed to be independent, and measurement noises are uncorrelated, with covariance given by

$$E[\boldsymbol{v}_i(k)\boldsymbol{v}_j^{\mathrm{T}}(k)] = R_i(k)\delta_{ij} \qquad i, j = 1, 2 \quad (11)$$

Denote $\hat{\boldsymbol{X}}_{j,k} = E\boldsymbol{X}_k$, $j = 1, 2$ as the unbiased estimation of the MS statement from each subfilter at time step k, where $\boldsymbol{X}_k$ is the true statement value at time step k, and $\hat{\boldsymbol{P}}_{ij}(k) = E\{(\boldsymbol{X}_k - \hat{\boldsymbol{X}}_{j,k})(\boldsymbol{X}_k - \hat{\boldsymbol{X}}_{i,k})^{\mathrm{T}}\} = \hat{\boldsymbol{P}}_{j,k}\delta_{ij}$, $i, j = 1, 2$ as the error covariance matrix at time step k. Thus a global optimal estimation of the MS statement can be achieved by weighted optimal data fusion. In this paper, we use the simplified UKF estimator as the subfilters to fulfill the local filtering work, which give local estimations $\hat{\boldsymbol{X}}_{j,k}$ and $\hat{\boldsymbol{P}}_{ij}(k)$, and apply the scalar weighted optimal fusion approach in the main estimator to obtain the global filtering results $\hat{\boldsymbol{X}}_{\mathrm{g},k}$ and $\hat{\boldsymbol{P}}_{\mathrm{g},k}$. The detailed description of the proposed algorithm is presented in section 2.

2 Federated UKF Algorithm for MS Estimation

2.1 Simplified UKF

The UKF is proved to be a superior alternative to the extended Kalman filter (EKF) for nonlinear systems[10-12]. By virtue of the unscented transformation (UT) and chosen sampling points (sigma points), the UKF is easily implemented and can predict the state of any nonlinearity with a second order accuracy or more.

Compared with the UKF algorithm suggested in Ref. [10], the simplified UKF avoids augmenting the state vector with the process and measurement noise terms, and thus it can obtain lower computation complexity and is easier to implement[11-12]. Using the symmetry sampling strategy[10], the proposed simplified UKF algorithm involves the following steps:

1) Initialization

$$\hat{\boldsymbol{X}}_0 = E(\boldsymbol{x}_0) \quad (12)$$

$$\hat{\boldsymbol{P}}_0 = E\{(\boldsymbol{X}_0 - \hat{\boldsymbol{X}}_0)(\boldsymbol{X}_0 - \hat{\boldsymbol{X}}_0)^{\mathrm{T}}\} \quad (13)$$

2) Calculation of sigma points $\boldsymbol{\chi}_{k-1}$ $(k = 1, 2, \ldots)$

$$\boldsymbol{\chi}_{k-1} = [\hat{\boldsymbol{X}}_{k-1} \ \ldots \ \hat{\boldsymbol{X}}_{k-1}] + \sqrt{n+\lambda}\,[0 \quad \sqrt{\hat{\boldsymbol{P}}_{k-1}} \quad -\sqrt{\hat{\boldsymbol{P}}_{k-1}}] \quad (14)$$

where n is the dimension of the state vector; $\lambda = \alpha^2(n+\kappa) - n$, and $\alpha, \kappa > 0$ are scaling parameters for the UT.

3) Time update

The predicted state mean $\hat{\boldsymbol{X}}_k^-$ and the predicted covariance $\hat{\boldsymbol{P}}_k^-$ are computed as

$$\hat{\boldsymbol{\chi}}_k = f(\boldsymbol{\chi}_{k-1}, k-1) \quad (15)$$

$$\hat{\boldsymbol{X}}_k^- = \hat{\boldsymbol{\chi}}_k \boldsymbol{\omega}_{\mathrm{m}} \quad (16)$$

$$\hat{\boldsymbol{P}}_k^- = \hat{\boldsymbol{\chi}}_k \boldsymbol{W} \hat{\boldsymbol{\chi}}_k^{\mathrm{T}} + \boldsymbol{Q}_{k-1} \quad (17)$$

where $\boldsymbol{\omega}_{\mathrm{m}} = \{W_{\mathrm{m}}^{(0)}, \ldots, W_{\mathrm{m}}^{(2n)}\}$ is the weight vector, and $\boldsymbol{W} = (\boldsymbol{I} - \{\boldsymbol{\omega}_{\mathrm{m}}, \ldots, \boldsymbol{\omega}_{\mathrm{m}}\}) \times \mathrm{diag}(W_{\mathrm{c}}^{(0)}, \ldots, W_{\mathrm{c}}^{(2n)}) \times (\boldsymbol{I} - \{\boldsymbol{\omega}_{\mathrm{m}}, \ldots, \boldsymbol{\omega}_{\mathrm{m}}\})^{\mathrm{T}}$ is the weight matrix of the $2n+1$ sigma points. The definitions of $W_{\mathrm{m}}^{(i)}$, $W_{\mathrm{c}}^{(i)}$, $i = 0, 1, \ldots, 2n$ can be found in Ref.

[11], with $\beta > 0$ as a scaling parameter.

4) Measurement update

The predicted mean of the measurement $\hat{\boldsymbol{Y}}_k^-$, the covariance of the measurement $\boldsymbol{S}_k$, and the cross-covariance of the state and measurement $\boldsymbol{C}_k$ are computed as

$$\boldsymbol{\chi}_k^- = [\hat{\boldsymbol{X}}_k^- \quad \dots \quad \hat{\boldsymbol{X}}_k^-] + \sqrt{n+\lambda}\,[0 \quad \sqrt{\hat{\boldsymbol{P}}_k^-} \quad -\sqrt{\hat{\boldsymbol{P}}_k^-}] \tag{18}$$

$$\boldsymbol{Y}_k^- = \boldsymbol{H}(\boldsymbol{\chi}_k^-, k) \tag{19}$$

$$\hat{\boldsymbol{Y}}_k^- = \boldsymbol{Y}_k^- \boldsymbol{\omega}_{\mathrm{m}} \tag{20}$$

$$\boldsymbol{S}_k = \boldsymbol{Y}_k^- \boldsymbol{W}(\boldsymbol{Y}_k^-)^{\mathrm{T}} + \boldsymbol{R}(k) \tag{21}$$

$$\boldsymbol{C}_k = \boldsymbol{\chi}_k^- \boldsymbol{W}(\boldsymbol{Y}_k^-)^{\mathrm{T}} \tag{22}$$

Then the filter gain $\boldsymbol{K}_k$, the updated state mean $\hat{\boldsymbol{X}}_k$, and updated covariance $\hat{\boldsymbol{P}}_k$ are computed as

$$\boldsymbol{K}_k = \boldsymbol{C}_k \boldsymbol{S}_k^{-1} \tag{23}$$

$$\hat{\boldsymbol{X}}_k = \hat{\boldsymbol{X}}_k^- + \boldsymbol{K}_k(\boldsymbol{y}_k - \hat{\boldsymbol{Y}}_k^-) \tag{24}$$

$$\hat{\boldsymbol{P}}_k = \hat{\boldsymbol{P}}_k^- - \boldsymbol{K}_k \boldsymbol{S}_k \boldsymbol{K}_k^{\mathrm{T}} \tag{25}$$

where for the j-th subfilter ($j = 1, 2$), we obtain

$$\boldsymbol{Q}_{k-1} = \boldsymbol{Q}_{j,k-1}, \ \boldsymbol{H}(\boldsymbol{\chi}_k^-, k) = \boldsymbol{H}_j(\boldsymbol{\chi}_k^-, k), \ \boldsymbol{R}(k) = \boldsymbol{R}_j(k)$$

$$\boldsymbol{y}_k = \boldsymbol{y}_k^{(j)}, \quad \hat{\boldsymbol{X}}_k = \hat{\boldsymbol{X}}_{j,k}, \quad \hat{\boldsymbol{P}}_k = \hat{\boldsymbol{P}}_{j,k}$$

2.2 Federated filtering and data fusion

In order to efficiently recombine and fuse the subfilter outputs and obtain an enhanced estimation result for the MS, the scalar weighted optimal fusion method[7] is used. Assuming that the measurement noises between the two subsystems are uncorrelated as discussed in section 1, the federated filtering and data fusion algorithm can be presented with the following steps:

1) Initialization

Denote the initial estimation value $\hat{\boldsymbol{X}}_{j,0}$, the covariance matrix $\hat{\boldsymbol{P}}_{j,0}$ and the process noise covariance $\boldsymbol{Q}_{j,0}$ of the subfilters according to the information distributing strategy, and assume the irrelevance of the estimations between the subfilters.

$$\hat{\boldsymbol{X}}_{j,0} = \hat{\boldsymbol{X}}_{\mathrm{g},0}, \quad \hat{\boldsymbol{P}}_{j,0} = a_j^{-1}\hat{\boldsymbol{P}}_{\mathrm{g},0}, \quad \boldsymbol{Q}_{j,0} = a_j^{-1}\boldsymbol{Q}_0 \tag{26}$$

$$\sum_j a_j = 1 \tag{27}$$

where $a_j, j = 1, 2$ is the information distributing parameter; $\hat{\boldsymbol{X}}_{j,0}, \hat{\boldsymbol{P}}_{\mathrm{g},0}, \hat{\boldsymbol{Q}}_{j,0}$ are initial estimation, covariance and process noise covariance prior information of the system.

2) Time update of each subfilter

Perform time update in each subfilter, and compute the predicted state mean and the predicted covariance of each subfilter as Eqs. (15) to (17).

3) Measurement update of each subfilter

Perform measurement update in each subfilter, and compute the updated state mean $\hat{\boldsymbol{X}}_{j,k}$ and the updated covariance $\hat{\boldsymbol{P}}_{j,k}$ of each subfilter as Eqs. (18) to (25).

4) Data fusion

Calculate the information distributing parameter $a_j, j = 1, 2$ at step k as

$$a_j = \Big(\sum_j \frac{1}{\mathrm{tr}\hat{\boldsymbol{P}}_{j,k}}\Big)^{-1}\frac{1}{\mathrm{tr}\hat{\boldsymbol{P}}_{j,k}} \qquad j = 1, 2 \tag{28}$$

where $\mathrm{tr}\hat{\boldsymbol{P}}_{j,k}$ represents the trace of the covariance matrix $\hat{\boldsymbol{P}}_{j,k}$. Then fuse the subfilter outputs and calculate the global estimation and error covariance value of time step k according to the scalar weighted optimal fusion rule as

$$\hat{\boldsymbol{X}}_{\mathrm{g},k} = \sum_j a_j \hat{\boldsymbol{X}}_{j,k} \tag{29}$$

$$\hat{\boldsymbol{P}}_{\mathrm{g},k} = \sum_j a_j^2 \hat{\boldsymbol{P}}_{j,k} \tag{30}$$

5) Feedback and information reset for each subfilter

Reset the estimation value $\hat{\boldsymbol{X}}_{j,k}$, the covariance matrix $\hat{\boldsymbol{P}}_{j,k}$ and the process noise covariance $\boldsymbol{Q}_{j,k}$ of the subfilters according to the information distributing strategy for estimation of time step $k+1$.

$$\hat{\boldsymbol{X}}_{j,k} = \hat{\boldsymbol{X}}_{\mathrm{g},k}, \quad \hat{\boldsymbol{P}}_{j,k} = a_j^{-1}\hat{\boldsymbol{P}}_{\mathrm{g},k}, \quad \boldsymbol{Q}_{j,k} = a_j^{-1}\boldsymbol{Q}_k \tag{31}$$

6) Repeat steps 2) to 5), until the mobile tracking and estimation at one time is finished.

3 Simulation Results

Simulation results are provided to assess the performance of the proposed algorithm. Assume that the MS can receive the signals from four BSs all the time. The BSs are located at (0, 0), (3 km, 0), (1.5 km, 3 km), (4.5 km, 3 km). The mobile trajectories and process noises are generated according to the Singer model described in section 1, in which the initial position of the MS is (150 m, 150 m), the initial velocity is $\dot{x}_0 = 15$ m/s, $\dot{y}_0 = 10$ m/s, the reciprocal of the acceleration time constant is $\alpha = 0.8$, the variance of MS acceleration is $\sigma_{\mathrm{m}}^2 = 25.6$. Set the sampling interval to be $T = 0.05$ s and the simulation step number be 1 000. Let the TDOA measurement noise be an additive zero-mean white Gaussian noise with standard variance $\sigma_1 = 30$ m and covariance $R_1 = {\sigma_1}^2 I$. Let the Doppler measurement noise be an additive zero-mean white Gaussian noise with standard variance $\sigma_2 = 4$ m/s and covariance $R_2 = {\sigma_2}^2 I$. The scaling parameters for the simplified UKF subfilters are chosen to be $\alpha = 0.2$, $\beta = 2$, $\kappa = 3 - n$; $n = 6$ is the dimension of the MS state. The initial estimation value of the MS is assumed to be $\hat{\boldsymbol{X}}_{\mathrm{g},0} = \{1, 1, 0, 1, 1, 0\}^{\mathrm{T}}$; the initial covariance matrix $\hat{\boldsymbol{P}}_{j,0} = \mathrm{diag}(6, 16, 1, 6, 16, 1)$; the initial information distributing parameter $a_1 = a_2 = 1/2$.

Fig. 2 shows the estimated and actual trajectories of the MS in the last 200 simulation steps by the simplified UKF algorithm with the TDOA measurement, the simplified UKF algorithm with the Doppler measurement, and the proposed federated UKF algorithm. It can be seen from the results that the proposed filtering fusion method has better estimation accuracy than the Doppler-UKF method, with its curve being smoother than the TDOA-UKF method.

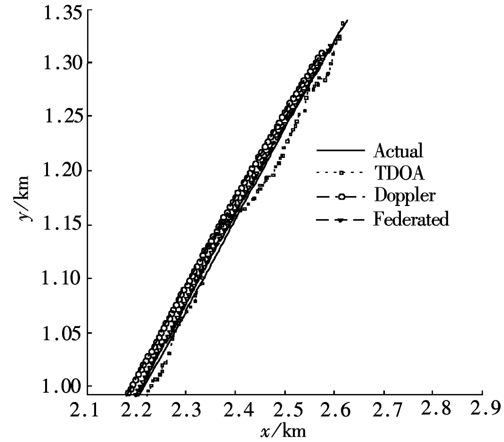

Fig. 2 The estimated and actual trajectories of the MS by three algorithms from a single realization

Fig. 3 displays the position root mean square error (RMSE) vs. time instant step by the three algorithms through 20 Monte Carlo simulations. The position RMSE at time step k is defined as

$$R_k = \sqrt{\frac{1}{M}\sum_{m=1}^{M}[(\hat{x}_{m,k} - x_k)^2 + (\hat{y}_{m,k} - y_k)^2]} \quad (32)$$

where M is the number of the Monte Carlo runs. The result demonstrates that the estimation error and variance performance is effectively mitigated by the proposed method compared with using the simplified UKF with TDOA or Doppler alone.

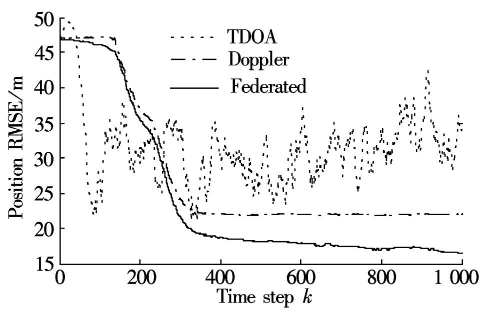

Fig. 3 Comparison of position RMSE vs. time instant step

Fig. 4 gives the comparison of position mean error CDF performance of the three methods through 20 Monte Carlo simulations. The position mean error at time step k is defined as

$$M_k = \frac{1}{M}\sum_{m=1}^{M}\sqrt{[(\hat{x}_{m,k} - x_k)^2 + (\hat{y}_{m,k} - y_k)^2]} \quad (33)$$

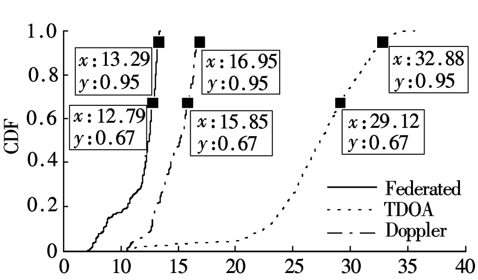

Fig. 4 Comparison of position mean error CDF

It can be clearly seen that the location estimation error of the TDOA-UKF method is within 29.12 m by 67%, and 32.88 m by 95%. The location estimation error of the Doppler-UKF method is within 15.85 m by 67%, and 16.95 m by 95%. The location estimation error of the proposed algorithm is within 12.79 m by 67%, and 13.29 m by 95%. The CDF performance evaluation result further validates the superiority of the proposed algorithm over the other two methods.

4 Conclusion

A federated filter method with TDOA and Doppler measurements based on the simplified UKF is proposed. The suggested algorithm has three advantages. First, the application of the federated filtering structure allows global optimal fusion of different measurements to be achieved with faster convergence. Secondly, the employment of the simplified UKF as a subfilter improves the performance in solving nonlinear problems compared with the traditional KF or EKF methods. Finally, the use of the scalar weighted optimal fusion method in the main estimator makes the algorithm easier to realize and more applicable compared with the matrix weighted fusion method. The simulation results validate the efficiency of the presented algorithm in mitigating the estimation error and variance, and enhancing the RSME and position mean error CDF performance for MS location positioning. Further work will emphasize solving the problem of correlations between the subsystems or the measurements in communications networks, which will be better employed to achieve accurate mobile tracking and estimation performance.

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基于 TDOA/Doppler 测量的联邦 UKF 移动位置估计算法

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摘要:为了进一步提高移动台的跟踪和定位性能,提出了一种基于联邦滤波结构和简化 UKF 的移动位置最优估计与融合新方法. 该算法以 Singer 移动台运动模型作为参考系统,以简化 UKF 滤波器作为子滤波器,对 2 组独立检测的 TDOA 和 Doppler 测量值进行局部估计;然后在主滤波器中,对子滤波器的估计结果按标量加权进行最优融合,得到全局最优或次最优融合估计结果;最后主滤波器利用全局估计结果对子滤波器和参考系统进行反馈和信息重置,以进行下一步估计. 仿真试验中,对该算法用于移动台位置估计的效果和性能进行评估,并与基于 TDOA 和基于 Doppler 的简化 UKF 方法做比较. 仿真结果表明,该算法能有效降低移动台位置估计的误差和方差,具有良好的均方根误差和均值误差 CDF 性能.

关键词:数据融合;移动位置估计;联邦滤波;无迹卡尔曼滤波器

中图分类号:TN957. 51