Uniform Acceleration Motion Target Location and Tracking Based on Time-Frequency Difference

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Abstract. In this paper, the problem of locating and tracking moving target with uniform acceleration by moving multi-stations is studied. Based on the time-difference information and frequency-difference information of target signal arriving at different base stations, a method of locating and tracking aerial moving target based on time-frequency difference is proposed. This method is based on extended kalman filter (EKF) and unscented kalman filter (UKF) filtering algorithms respectively to locate and track moving target, and compares the locating results of the two algorithms. This method can not only locate and track the aerial target, but also estimate the velocity and acceleration information of the target. The simulation results show that the location and tracking results of this method can achieve high positioning accuracy, and the positioning accuracy of UKF is better than that of EKF and better positioning results can be obtained, which has a certain reference value for the engineering realization of multi-station moving target location and tracking in the air.

Keywords: Time-frequency difference location · EKF · UKF

1 Introduction

Target location and tracking [1] is a technique for estimating target motion state based on telemetry data. At any time, there is an urgent need for situational awareness [2] and prediction ability of moving targets, and the monitoring ability of existing equipment for moving targets is still very limited. In order to realize situational awareness and prediction ability of moving targets, it is necessary to use all available means to

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reconnaissance these threatening targets and control their related information, including location information, velocity information and acceleration information.

According to the different types of observers, the target localization technology is generally divided into active localization [3] and passive localization [4]. Passive location technology is essentially the fusion of location method and location algorithm. Passive location methods mainly include direction finding cross location [5], time difference location [6], time-frequency difference location [7] and so on. In this paper, the joint location technology of time difference and frequency difference is adopted. This technology can improve the positioning accuracy of the target. In this paper, EKF [8] and UKF [9] filtering methods are applied to locate and track the target according to the characteristics of time-frequency difference location method and the moving state of the target, i.e. uniformly accelerated motion model, and the simulation results are given.

The rest of this paper is structured as follows. The second section describes the principle of time-frequency difference location and tracking. The third section describes the filtering algorithm. The fourth section simulates and analyses the performance of the algorithm, and makes a comparison. Section 5 summarizes the full text.

2 Principle of Time-Frequency Difference Location and Tracking

Passive Time-Frequency-Difference localization technology locates the target according to the time difference of arrival (TDOA) and frequency difference of arrival (FDOA) measured by the observation station. In order to locate the target, first of all, we need to establish a location model.

The position, velocity and acceleration of the target emitter respectively are $\mathbf{p}(t) = [x(t), y(t), z(t)]^T$, $\dot{\mathbf{p}}(t) = [\dot{x}(t), \dot{y}(t), \dot{z}(t)]^T$, $\ddot{\mathbf{p}}(t) = [\ddot{x}(t), \ddot{y}(t), \ddot{z}(t)]^T$. The position, velocity and acceleration of M observation stations respectively are $\mathbf{s}_i(t) = [x_i(t), y_i(t), z_i(t)]^T$, $\dot{\mathbf{s}}_i(t) = [\dot{x}_i(t), \dot{y}_i(t), \dot{z}_i(t)]^T$, $\ddot{\mathbf{s}}_i(t) = [\ddot{x}_i(t), \ddot{y}_i(t), \ddot{z}_i(t)]^T$, $i = 1, \cdots, M$.

The distance between the radiation source and each observatory is as follows:

$$r_i(t) = \|\mathbf{p}(t) - \mathbf{s}(t)\| = \sqrt{(x(t) - x_i(t))^2 + (y(t) - y_i(t))^2 + (z(t) - z_i(t))^2} \tag{1}$$

Suppose f_c is the center frequency of the target signal. With the first observatory as the reference station, the TDOA and FDOA measurements between the radiation source and the i observatory and the reference station are obtained:

$$\tau_{i1}(t) = \tau_i(t) - \tau_1(t) + \Delta\tau_{i1} = \frac{r_i(t) - r_1(t)}{c} + \Delta\tau_{i1},\ i = 2, \cdots, M \tag{2}$$

$$\begin{aligned} f_{i1}(t) &= f_i(t) - f_1(t) + \Delta f_{i1} \\ &= \frac{f_c}{c}\left[\frac{(\mathbf{p}(t) - \mathbf{s}_i(t))^T(\dot{\mathbf{p}}(t) - \dot{\mathbf{s}}_i(t))}{\|(\mathbf{p}(t) - \mathbf{s}_i(t))\|_2} - \frac{(\mathbf{p}(t) - \mathbf{s}_1(t))^T(\dot{\mathbf{p}}(t) - \dot{\mathbf{s}}_1(t))}{\|(\mathbf{p}(t) - \mathbf{s}_1(t))\|_2}\right] + \Delta f_{i1} \end{aligned} \tag{3}$$

Among them, $\Delta\tau_{i1}$ represents the TDOA measurement error between the first observation station and the i observation station, and obeys the normal distribution of zero mean and variance δ_τ^2. Δf_{i1} represents the FDOA measurement error between the first observatory and the i observatory station, and obeys the normal distribution of zero mean and variance δ_f^2.

Formulas (2) and (3) are combined, that is, time-frequency difference equations. The position information of the target can be obtained by solving the equations, but the velocity and acceleration information of the target can not be obtained. Velocity and acceleration information can be obtained by filtering.

3 CRLB (Cramer-Rao Lower Bound)

As shown in the previous section, τ_{i1} obeys the normal distribution with mean $\tau_i - \tau_1$ and variance δ_τ^2, and its joint probability density distribution is as follows:

$$p(\mathbf{p}(t)) = \frac{1}{\left(2\pi\delta_\tau^2\right)^{(M-1)/2}} \boldsymbol{exp}\left[-\frac{1}{2\delta_\tau^2}\sum_{i=2}^{M}\left(\tau_{i1} - (\tau_i - \tau_1)\right)^2\right]$$

f_{i1} obeys the normal distribution with mean $f_i - f_1$ and variance δ_f^2, and its joint probability density distribution is as follows:

$$p(\mathbf{p}(t), \dot{\mathbf{p}}(t)) = \frac{1}{\left(2\pi\delta_f^2\right)^{(M-1)/2}} \boldsymbol{exp}\left[-\frac{1}{2\delta_f^2}\sum_{i=2}^{M}\left(f_{i1} - (f_i - f_1)\right)^2\right]$$

The joint probability density distributions of the above two are as follows:

$$\begin{aligned} & p(\mathbf{p}(t), \dot{\mathbf{p}}(t)) \\ & = \frac{1}{\left(4\pi^2\delta_\tau^2\delta_f^2\right)^{(M-1)/2}} \boldsymbol{exp}\left[-\frac{1}{2\delta_\tau^2}\sum_{i=2}^{M}\left(\tau_{i1} - (\tau_i - \tau_1)\right)^2 - \frac{1}{2\delta_f^2}\sum_{i=2}^{M}\left(f_{i1} - (f_i - f_1)\right)^2\right] \end{aligned}$$

Let $\boldsymbol{\theta} = [\,\mathbf{p}(t) \quad \dot{\mathbf{p}}(t)\,] = [\,x \quad y \quad z \quad \dot{x} \quad \dot{y} \quad \dot{z}\,]^T$, $\mathbf{g} = [\,\tau_2 - \tau_1 \quad \cdots \quad \tau_M - \tau_1 \quad f_2 - f_1 \cdots f_M - f_1]^T$.

The Jacobian matrix is:

$$\mathbf{J} = \frac{\partial \mathbf{g}}{\partial \boldsymbol{\theta}} = \begin{bmatrix} \frac{\partial \mathbf{g}_1}{\partial \boldsymbol{\theta}_1} & \cdots & \frac{\partial \mathbf{g}_1}{\partial \boldsymbol{\theta}_6} \\ \vdots & \vdots & \vdots \\ \frac{\partial \mathbf{g}_M}{\partial \boldsymbol{\theta}_1} & \cdots & \frac{\partial \mathbf{g}_M}{\partial \boldsymbol{\theta}_6} \end{bmatrix}$$

The variance of the observed noise is: $\mathbf{Q}_2 = diag\left[\underbrace{\delta_\tau^2 \cdots \delta_\tau^2}_{M-1}, \underbrace{\delta_f^2 \cdots \delta_f^2}_{M-1}\right]$

From this, we can get Fisher Information $\mathbf{F}(\boldsymbol{\theta})$: $\mathbf{F}(\boldsymbol{\theta}) = \mathbf{J}^T\mathbf{Q}_2^{-1}\mathbf{J}$.
Therefore, CRLB is: $CRLB(\boldsymbol{\theta}) = \mathbf{F}^{-1}$.

4 Filtering Process

The non-linearity of target location and tracking problem originates from the non-linearity of function in state equation and observation equation and the non-Gaussian of related noise process, so the prerequisite of Kalman filter is not satisfied.

The moving target adopts uniform acceleration motion model, and its motion state equation is as follows:

$$\begin{cases} x(t) = x(t-T) + T\dot{x}(t-T) + \frac{T^2}{2}\ddot{x}(t-T) + \frac{T^2}{2}\delta_x(t-T) \\ \dot{x}(t) = \dot{x}(t-T) + T\ddot{x}(t-T) + T\delta_x(t-T) \\ \ddot{x}(t) = \ddot{x}(t-T) + \delta_x(t-T) \\ y(t) = y(t-T) + T\dot{y}(t-T) + \frac{T^2}{2}\ddot{y}(t-T) + \frac{T^2}{2}\delta_y(t-T) \\ \dot{y}(t) = \dot{y}(t-T) + T\ddot{y}(t-T) + T\delta_y(t-T) \\ \ddot{y}(t) = \ddot{y}(t-T) + \delta_y(t-T) \\ z(t) = z(t-T) + T\dot{z}(t-T) + \frac{T^2}{2}\ddot{z}(t-T) + \frac{T^2}{2}\delta_z(t-T) \\ \dot{z}(t) = \dot{z}(t-T) + T\ddot{z}(t-T) + T\delta_z(t-T) \\ \ddot{z}(t) = \ddot{z}(t-T) + \delta_z(t-T) \end{cases} \tag{4}$$

Among them, T is the time interval, $\delta_x(t)$, $\delta_y(t)$ and $\delta_z(t)$ are the interference in x, y and z directions respectively, which can be regarded as system noise.

The equation of state of the system can be described as:

$$\mathbf{x}(n) = \mathbf{F}(n, n-1)\mathbf{x}(n-1) + \Gamma(n, n-1)\mathbf{v}_1(n-1) \tag{5}$$

Among them,

$$\mathbf{x}(n) = [x(n)\ \mathrm{y}(n)\ \mathrm{z}(n)\ \dot{x}(n)\ \dot{\mathrm{y}}(n)\ \dot{\mathrm{z}}(n)\ \ddot{x}(n)\ \ddot{\mathrm{y}}(n)\ \ddot{\mathrm{z}}(n)] \tag{6}$$

$$\mathbf{F}(n, n-1) = \begin{bmatrix} 1 & 0 & 0 & T & 0 & 0 & \frac{T^2}{2} & 0 & 0 \\ 0 & 1 & 0 & 0 & T & 0 & 0 & \frac{T^2}{2} & 0 \\ 0 & 0 & 1 & 0 & 0 & T & 0 & 0 & \frac{T^2}{2} \\ 0 & 0 & 0 & 1 & 0 & 0 & T & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & T & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & T \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$\Gamma(n, n-1) = \begin{bmatrix} \frac{T^2}{2} & 0 & 0 & T & 0 & 0 & 1 & 0 & 0 \\ 0 & \frac{T^2}{2} & 0 & 0 & T & 0 & 0 & 1 & 0 \\ 0 & 0 & \frac{T^2}{2} & 0 & 0 & T & 0 & 0 & 1 \end{bmatrix}^T$$

$$\mathbf{v}_1(n-1) = \left[\delta_x(n-1)\ \delta_y(n-1)\ \delta_z(n-1)\right]^{\mathrm{T}}$$

The variance of system noise is

$$\mathbf{Q}_1(n) = E\left[\mathbf{v}_1(n)\,\mathbf{v}_1(n)^T\right] = diag\left[\delta_x^2, \delta_y^2, \delta_z^2\right].$$

The observation equation of the system is as follows:

$$\begin{aligned}\mathbf{z}(n) &= \mathbf{h}(n) + \mathbf{v}_2(n) \\ &= [\tau_{21}(n)\ \cdots\ \tau_{M1}(n)\ f_{21}(n)\ \cdots\ f_{M1}(n)]^T + \mathbf{v}_2(n)\end{aligned} \tag{7}$$

Among them, $\mathbf{v}_2(n)$ is the observation noise and its variance is

$$\mathbf{Q}_2(n) = E\left[\mathbf{v}_2(n)\,\mathbf{v}_2(n)^T\right] = diag\left[\underbrace{\delta_\tau^2 \cdots \delta_\tau^2}_{M-1}, \underbrace{\delta_f^2 \cdots \delta_f^2}_{M-1}\right]$$

The Jacobian matrix of the measurement equation is:

$$\begin{aligned}\mathbf{H}(n) &= \frac{\partial \mathbf{h}(n)}{\partial \hat{\mathbf{x}}(n|L_{n-1})} \\ &= \begin{bmatrix} \frac{\partial \tau_{i1}}{\partial \hat{x}(n|L_{n-1})} & \frac{\partial \tau_{i1}}{\partial \hat{y}(n|L_{n-1})} & \frac{\partial \tau_{i1}}{\partial \hat{z}(n|L_{n-1})} & 0 & 0 & 0 & 0 & 0 & 0 \\ \frac{\partial f_{i1}}{\partial \hat{x}(n|L_{n-1})} & \frac{\partial f_{i1}}{\partial \hat{y}(n|L_{n-1})} & \frac{\partial f_{i1}}{\partial \hat{z}(n|L_{n-1})} & \frac{\partial f_{i1}}{\partial \hat{\dot{z}}(n|L_{n-1})} & \frac{\partial f_{i1}}{\partial \hat{\dot{y}}(n|L_{n-1})} & \frac{\partial f_{i1}}{\partial \hat{\dot{z}}(n|L_{n-1})} & 0 & 0 & 0 \end{bmatrix}\end{aligned}$$

EKF filtering model and UKF filtering model are composed of (5) equation of state and (7) equation of observation to track moving target. The EKF filtering process is as follows:

(1) Initialization of filtering:

$$\begin{aligned}&\hat{\mathbf{x}}(0|L_0) = E[\mathbf{x}(0)] \\ &\mathbf{P}(0) = E\left\{[\mathbf{x}(0) - E[\mathbf{x}(0)]][\mathbf{x}(0) - E[\mathbf{x}(0)]]^H\right\}\end{aligned}$$

(2) Further state prediction:

$$\hat{\mathbf{x}}(n|L_{n-1}) = \mathbf{F}(n, n-1)\hat{\mathbf{x}}(n-1|L_{n-1})$$

(3) One-step prediction state error autocorrelation matrix:

$$\mathbf{P}(n, n-1) = \mathbf{F}(n, n-1)\mathbf{P}(n-1)\mathbf{F}^H(n, n-1) + \Gamma(n, n-1)\mathbf{Q}_1(n-1)\Gamma^H(n, n-1)$$

(4) Kalman gain:

$$\mathbf{K}(n) = \mathbf{P}(n, n-1)\mathbf{H}^H(n)\left[\mathbf{H}(n)\mathbf{P}(n, n-1)\mathbf{H}^H(n)\mathbf{Q}_2(n)\right]^{-1}$$

(5) State estimation:

$$\hat{\mathbf{x}}(n|L_n) = \hat{\mathbf{x}}(n|L_{n-1}) + \mathbf{K}(n)[\mathbf{z}(n) - \mathbf{h}(\hat{\mathbf{x}}(n|L_{n-1}), n)]$$

(6) State estimation error autocorrelation matrix:

$$\mathbf{P}(n) = [\mathbf{I} - \mathbf{K}(n)\mathbf{H}(n)]\mathbf{P}(n, n-1)$$

(7) Repeat steps (1) to (6) to calculate the recursive filtering.

Taking proportional symmetric sampling as an example, The UKF filtering process is as follows:

(1) The filtering initialization is the same as that of EKF.
(2) After UT transformation, $2N_x + 1$ Sigma points are obtained:

$$\boldsymbol{\chi}(n) = \left[\mathbf{x}(n) - \left[\sqrt{(N_x + \lambda)\mathbf{P}(n)}\right]_i \cdots \mathbf{x}(n) \cdots \mathbf{x}(n) + \left[\sqrt{(N_x + \lambda)\mathbf{P}(n)}\right]_i\right]$$

$$i = 1, \cdots, N_x$$

In the formula, N_x denotes the dimension of the state estimation vector $\mathbf{x}(n)$. $\left[\sqrt{(N_x + \lambda)\mathbf{P}(n)}\right]_i$ represents the i column of the root of the matrix $(N_x + \lambda)\mathbf{P}(n)$. The corresponding sampling point weights are:

$$\begin{cases} W_0^m = \lambda/(L + \lambda) \\ W_0^c = \lambda/(L + \lambda) + (1 - \alpha^2 + \beta) \\ W_i^m = W_i^c = 1/[2(L + \lambda)], i = 1, \cdots, 2N_x \end{cases}$$

In the formula, m denotes the weight of the mean and c denotes the weight of the covariance. Parametric $\lambda = \alpha^2(N_x + \kappa) - N_x$ is a scaling parameter, which determines the distance between the sampling point and the mean value. The value range of α is $[10^{-4}, 1]$, which controls the distribution of sampling points. The value of κ needs to guarantee the semi-positive definiteness of matrix $(N_x + \lambda)\mathbf{P}(n)$, which is usually $3 - N_x$. β is a non-negative weight coefficient, usually takes the value of 2, which can combine the dynamic difference of higher-order terms in the equation improve the accuracy of calculation.

(3) One-step state prediction data set:

$$\boldsymbol{\chi}(n+1|L_n) = f(\boldsymbol{\chi}(n), n)$$

(4) The data set is weighted and merged to obtain a one-step state prediction vector:

$$\hat{\mathbf{x}}(n+1|L_n) = \sum_{i=0}^{2N_x} W_i^{(m)} \boldsymbol{\chi}_i(n+1|L_n)$$

(5) One-step state prediction error autocorrelation matrix:

$$\mathbf{P}(n+1|L_n) = \sum_{i=0}^{2N_x} W_i^{(c)} \left[\boldsymbol{\chi}_i(n+1|L_n) - \hat{\mathbf{x}}(n+1|L_n)\boldsymbol{\chi}_i(n+1|L_n) - \hat{\mathbf{x}}(n+1|L_n)^T\right] + \mathbf{Q}_1$$

(6) Repeat UT transform to get a new set of sigma points:

$$\mathbf{Z}(n+1|L_n) = h(\boldsymbol{\chi}(n+1|L_n), n+1)$$

$$\hat{\mathbf{z}}(n+1|L_n) = \sum_{i=0}^{2N_x} W_i^{(m)} \mathbf{Z}_i(n+1|L_n)$$

$$\mathbf{P}_{zz}(n+1|L_n) = \sum_{i=0}^{2N_x} W_i^{(m)} [\mathbf{Z}_i(n+1|L_n) - \hat{\mathbf{z}}(n+1|L_n)][\mathbf{Z}_i(n+1|L_n) - \hat{\mathbf{z}}(n+1|L_n)]^T + \mathbf{Q}_2$$

(7) The cross-correlation matrix of the state vector and the observation vector is:

$$\mathbf{P}_{xz}(n+1|L_n) = \sum_{i=0}^{2N_x} W_i^{(m)} [\boldsymbol{\chi}_i(n+1|L_n) - \hat{\mathbf{x}}(n+1|L_n)][\mathbf{Z}_i(n+1|L_n) - \hat{\mathbf{z}}(n+1|L_n)]^T$$

(8) Kalman gain and state update:

$$\mathbf{K}(n+1) = \mathbf{P}_{xz}(n+1|L_n)[\mathbf{P}_{zz}(n+1|L_n)]^{-1}$$

$$\hat{\mathbf{x}}(n+1|L_{n+1}) = \hat{\mathbf{x}}(n+1|L_n) + \mathbf{K}(n+1)[\mathbf{z}(n+1) - \hat{\mathbf{z}}(n+1|L_n)]$$

$$\mathbf{P}(n+1) = \mathbf{P}(n+1|L_n) - \mathbf{K}(n+1)\mathbf{P}_{zz}(n+1|L_n)\mathbf{K}^T(n+1).$$

5 Simulation

In order to verify the application effect of EKF and UKF filtering on moving target location and tracking, simulation analysis is carried out on MATLAB platform. Assume that the position of the target is (180, 170, 10) (km), the velocity is (0, 50, 0) (m/s), and the acceleration is (5, 0, 0) (m/s^2). The central frequency of the target signal is 1 GHz. Here, the number of observatories is 3 and the distribution is triangular. The locations are (30, 5, 0) (km), (40, 10, 0) (km), (50, 15, 0) (km), the velocities are (0, 10, 0) (m/s) and the accelerations are (0, 10, 0) (m/s^2). The time difference accuracy is

120 ns and the frequency difference accuracy is 2 Hz. Through the above filtering process, the filtering results are shown in Figs. 2 and 3.

Figure 1 is a schematic diagram of the trajectory of three base stations and their targets. The three base stations move in the same direction, i.e., the y-axis. The target moves in the x-axis direction. From Figs. 2 and 3, it can be seen that the method used in this paper can locate and track the trajectory of the target, and track the velocity and acceleration of the target at the same time. Moreover, it can achieve high positioning accuracy and estimation accuracy.

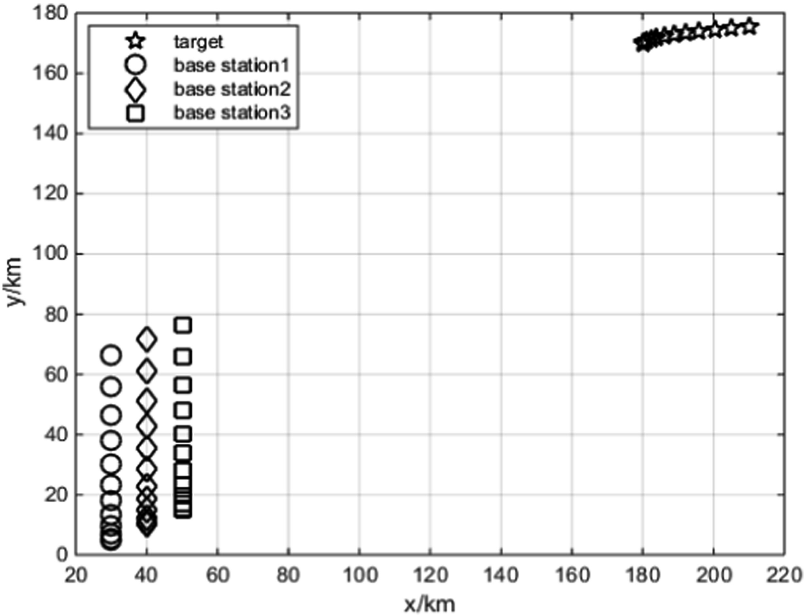

Fig. 1. Motion trajectory plan of base station and target

In the process of linearization, higher order terms are omitted. For strong nonlinear systems, the approximation accuracy of EKF is not high, so the estimation accuracy of EKF for strong nonlinear systems is poor. At the same time, the Jacobian matrix of some non-linear systems is not available, and EKF is only suitable for the case of small one-step prediction error of filtering error. These shortcomings limit the further development of EKF. UKF uses UT transformation to deal with the transfer of mean and covariance of nonlinear systems. The linearization of the nonlinear system is avoided, the higher order terms are retained, and the transmission accuracy of the system's Gauss density is improved. The simulation results show that UKF can obtain better positioning results, and can be used in the situation of long-term positioning and tracking of air moving targets.

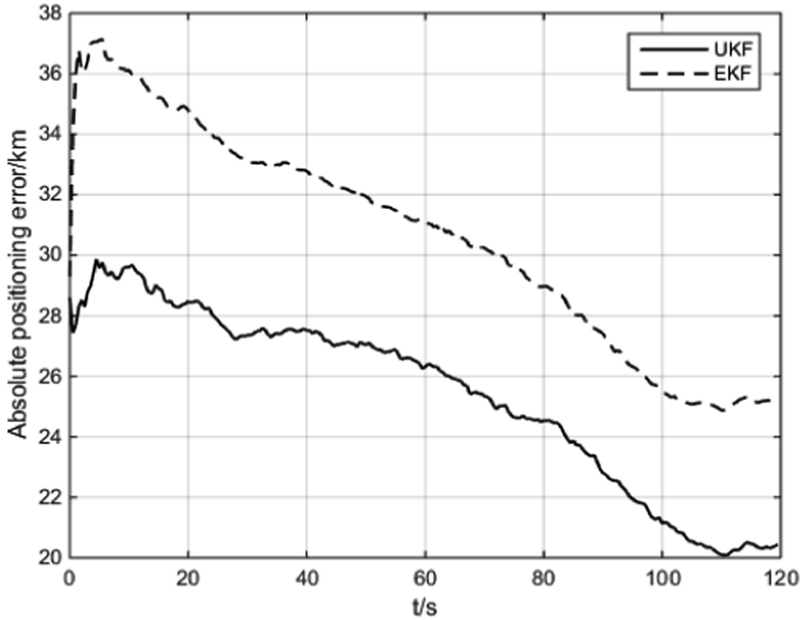

Fig. 2. Comparing the location error curves of EKF and UKF algorithms

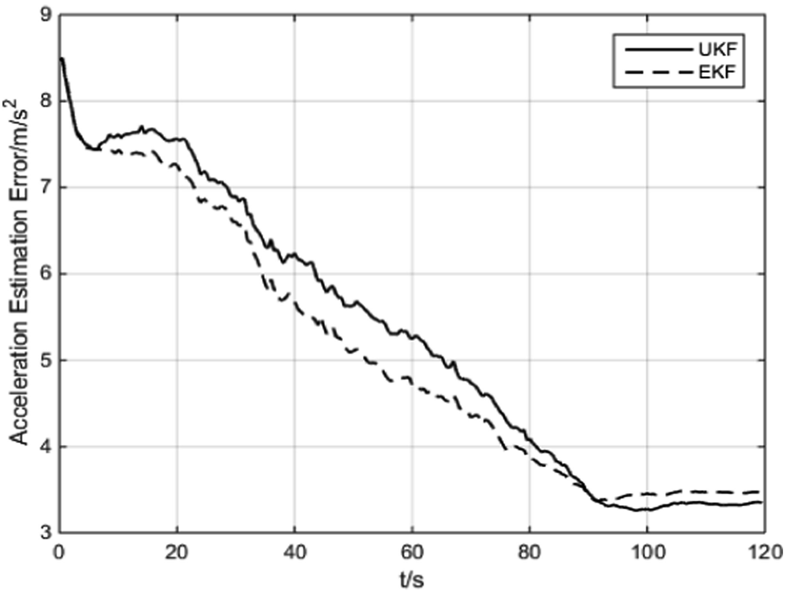

Fig. 3. Comparing the acceleration estimation error curves of EKF and UKF algorithms

6 Conclusion

In this paper, the problem of location and tracking of air moving targets by moving Multi-stations is studied. EKF method and UKF method are used to filter the time-frequency difference data. The moving target adopts uniform acceleration motion model to locate and track the target, and can estimate the velocity and acceleration information of the target at the same time. The simulation results show that UKF can achieve high positioning accuracy in location tracking, velocity estimation and acceleration estimation. It has a certain reference value for the engineering realization of the position tracking and velocity and acceleration estimation of aerial moving targets by moving multi-stations.

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