Research on a Strong Tracking GPS/SINS Deeply Integrated AUKF Filtering Method

Lin Han, Shuai Chen, Longjiang Fan

***Abstract*— Aiming at characteristics of Ballistic missile, the GPS/SINS deeply integrated navigation algorithm based on Strong Tracking Adaptive Unscented Kalman Filter (STAUKF) in the Launch inertial coordinates is studied in this paper. The algorithm is based on the thought of fading, by introducing suboptimal multiple fading matrix into UKF filter, perform real-time adjustment on the error covariance of predicted state adaptively, so as to achieve strong tracking of the rapidly changing state. Ballistic trajectory simulation results show that suboptimal multiple fading matrix were introduced into UKF can make better use of prior information and it has stronger tracking ability for highly maneuvering targets. The improved algorithm ensures the original UKF filtering algorithm accuracy, at the same time, the system error is shown to converge in a shorter period of time.**

***Index Terms*— Adaptive Unscented Kalman Filter, Launch inertial coordinates, Deeply integrated, Strong tracking**

I. INTRODUCTION

The deeply integrated navigation system based on GPS/SINS is a high-level integrated navigation method. It uses the samples in the in-phase or quadrature GPS receiver channel to update the state of the navigation filter. Carrier control and code generator also comes from the navigation filter output correction, which can obtain higher carrier phase tracking bandwidth and anti-interference ability. Deeply integrated navigation systems operate in highly dynamic and strong interference environments, and their correlator output is highly nonlinear [1].

Generally there are two methods for this nonlinear problem [2-3]. One is to linearize the nonlinear function and to ignore or approximate the higher order term. The most commonly used is the Extended Kalman Filter (EKF). The other filtering method to deal with nonlinear problems is to use a sampling method to approximate the nonlinear distribution, such as the Unscented Kalman Filter (UKF) algorithm [4-5], which can avoid the problem of complex computation of Jacobian matrix in EKF and other issues.

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However, these two algorithms have the problems of poor robustness and poor tracking ability in the case of inaccurate models or sudden changes in state. To solve this problem, Donghua Zhou proposed the concept of strong tracking filter (STF) based on the principle of orthogonality of innovation vectors, and applied it in the improvement of EKF. The strong tracking filter has better robustness to model uncertainty and stronger tracking ability with respect to mutation states [6].

This paper aims at the problem that the standard UKF lacks self-adaptive adjustment of system state anomalies, resulting in reduced filtering accuracy. And based on the basic UKF algorithm framework, meanwhile combined with the basic theory of strong tracking filtering and Sage filtering theory, establishes a strong tracking AUKF filtering algorithm with multiple suboptimal fading matrices. Through the introduction of multiple suboptimal fading matrices, the system measurement noise matrix can be re-estimated adaptively. This algorithm is applied to the simulation of GPS/SINS deeply integrated navigation under the launch inertial coordinate. And the results show that compared with the standard UKF, the proposed algorithm can better solve the problem that the state system and the measurement system suffer from the worsening of the accuracy of the interference, and has better estimation accuracy and adaptability.

II. PROBLEM DESCRIPTION AND UKF ALGORITHM

Both UKF and the standard Kalman Filter belong to the linear minimum difference estimation, and the algorithms are all based on the model. But unlike the standard Kalman Filter, the UKF algorithm determines the optimal gain matrix based on the covariance matrix measured by the estimator and quantity. The covariance matrix is calculated based on duplicated sample points. These sample points are determined based on the system equations and measurement equations. Therefore, UKF did not propose any additional conditions for the system equations and measurement equations in calculating the optimal gain matrix. The algorithm is suitable for both linear and nonlinear objects [7].

In this paper, considers the following discrete-time nonlinear systems:

$$\begin{cases} \boldsymbol{x}_{k+1} = \boldsymbol{f}(\boldsymbol{x}_k, \boldsymbol{u}_k) + \boldsymbol{v}_k \\ z_{k+1} = \boldsymbol{h}(\boldsymbol{x}_{k+1}) + \boldsymbol{w}_{k+1} \end{cases} \tag{1}$$

In the formula, $\boldsymbol{x}_k$ is the system state vector, z_{k+1} is the measurement vector, $\boldsymbol{f}(g)$ is the nonlinear state transfer function of the system, $\boldsymbol{h}(g)$ is the nonlinear measurement function of the system, $\boldsymbol{w}_k$ is the Gaussian white noise and $\boldsymbol{v}_k$ is the Gaussian white noise. Gaussian white noise satisfies the following statistical characteristics:

$$E[\boldsymbol{w}_n \boldsymbol{w}_k^{\mathrm{T}}] = \begin{cases} \boldsymbol{Q}_k, n = k \\ 0, n \neq k \end{cases} \quad E[\boldsymbol{v}_n \boldsymbol{v}_k^{\mathrm{T}}] = \begin{cases} \boldsymbol{R}_k, n = k \\ 0, n \neq k \end{cases} \tag{2}$$

Where: $\boldsymbol{Q}_k$ is the covariance matrix of $\boldsymbol{w}_k$, $\boldsymbol{R}_k$ is the covariance matrix of $\boldsymbol{v}_k$ and they are symmetrical and non-negative.

The specific processes of the standard UKF algorithm are as follows:

Step One: Initialization

Assume that the system's initial state x_0 is a random vector of Gaussian distribution. State initialization conditions:

$$\begin{cases} \hat{\boldsymbol{x}}_0 = \boldsymbol{E}(\boldsymbol{x}_0) \\ \boldsymbol{P}_0 = \boldsymbol{E}(\boldsymbol{x}_0 - \hat{\boldsymbol{x}}_0)(\boldsymbol{x}_0 - \hat{\boldsymbol{x}}_0)^{\mathrm{T}} \end{cases} \tag{3}$$

Step Two: Calculate sample points

For $n \geq 1$, in the case of only considering the mean $\hat{\boldsymbol{x}}$ and covariance $\boldsymbol{P}_k$ of the input variables, $\hat{\boldsymbol{x}}$ and $\boldsymbol{P}_k$ are approximated by Sigma points. The following $2n+1$ sampling points can be obtained from the sampling function of the Sigma point symmetrical sampling strategy:

$$\begin{cases} \tilde{\chi}_{0,k} = \hat{\boldsymbol{x}}_k & i = 0 \\ \tilde{\chi}_{i,k} = \hat{\boldsymbol{x}}_k + \sqrt{\mathrm{n}+\lambda}(\sqrt{\boldsymbol{P}_k})_i & i = 1, 2, \cdots, \mathrm{n} \\ \tilde{\chi}_{i,k} = \hat{\boldsymbol{x}}_k - \sqrt{\mathrm{n}+\lambda}(\sqrt{\boldsymbol{P}_k})_{i-\mathrm{n}} & i = \mathrm{n}+1, \cdots, 2\mathrm{n} \end{cases} \tag{4}$$

In the formula: $\left(\sqrt{\boldsymbol{P}_k}\right)_i$ is the i-th column of the root mean square of the matrix $\boldsymbol{P}_k$, which can be obtained by Cholesky decomposition. The determination of the proportional parameter λ is as follows:

$$\lambda = \alpha^2 (n + \kappa) - n \tag{5}$$

Where: α is a small positive number, it can be taken $10^{-4} \leq \alpha \leq 1; \kappa = 3 - n$.

Then determine the weight of sampling points:

$$\begin{cases} w_0^m = \dfrac{\lambda}{n+\lambda} \\ w_0^c = \dfrac{\lambda}{n+\lambda} + 1 - \alpha^2 + \beta \\ w_i^m = w_i^c = \dfrac{\lambda}{2(n+\lambda)}, i = 1, 2, \cdots, n \end{cases} \tag{6}$$

In the formula: The value of β is related to the distribution of $\boldsymbol{x}$. For a normal distribution, $\beta = 2$ is the optimal value.

Step Three: Prediction equations

$$\chi_{i,k+1|k}^{*} = \boldsymbol{f}\left(\tilde{\chi}_{i,k}\right) \tag{7}$$

$$\hat{\boldsymbol{x}}_{k+1|k} = \sum_{i=0}^{2\mathrm{n}} w_i^c \chi_{i,k+1|k}^{*} \tag{8}$$

$$\boldsymbol{P}_{k+1|k} = \sum_{i=0}^{2\mathrm{n}} w_i^c \left(\chi_{i,k+1|k}^{*} - \hat{\boldsymbol{x}}_{k+1|k}\right)\left(\chi_{i,k+1|k}^{*} - \hat{\boldsymbol{x}}_{k+1|k}\right)^{\mathrm{T}} + \boldsymbol{Q}_k \tag{9}$$

Step Four: Calculate one-step prediction sampling points

$$\begin{cases} \chi_{0,k+1|k} = \hat{\boldsymbol{x}}_{k+1|k} & i = 0 \\ \chi_{i,k+1|k} = \hat{\boldsymbol{x}}_{k+1|k} + \sqrt{\mathrm{n}+\lambda}(\sqrt{\boldsymbol{P}_{k+1|k}})_i & i = 1, 2, \cdots, \mathrm{n} \\ \chi_{i,k+1|k} = \hat{\boldsymbol{x}}_{k+1|k} - \sqrt{\mathrm{n}+\lambda}(\sqrt{\boldsymbol{P}_{k+1|k}})_{i-\mathrm{n}} & i = \mathrm{n}+1, \cdots, 2\mathrm{n} \end{cases} \tag{10}$$

$$\boldsymbol{z}_{i,k+1|k}^{*} = \boldsymbol{h}\left(\chi_{i,k+1|k}\right) \tag{11}$$

$$\hat{\boldsymbol{z}}_{k+1|k} = \sum_{i=0}^{2\mathrm{n}} w_i^m \boldsymbol{z}_{i,k+1|k}^{*} \tag{12}$$

Step Five: Update equations

$$\boldsymbol{P}_{zz,k+1|k} = \sum_{i=0}^{2\mathrm{n}} w_i^c \left(\boldsymbol{z}_{i,k+1|k}^{*} - \hat{\boldsymbol{z}}_{k+1|k}\right)\left(\boldsymbol{z}_{i,k+1|k}^{*} - \hat{\boldsymbol{z}}_{k+1|k}\right)^{\mathrm{T}} + \boldsymbol{R}_{k+1} \tag{13}$$

$$\boldsymbol{P}_{xz,k+1|k} = \sum_{i=0}^{2\mathrm{n}} w_i^c \left(\chi_{i,k+1|k}^{*} - \hat{\boldsymbol{x}}_{k+1|k}\right)\left(\boldsymbol{z}_{i,k+1|k}^{*} - \hat{\boldsymbol{z}}_{k+1|k}\right)^{\mathrm{T}} \tag{14}$$

$$\boldsymbol{K}_{k+1} = \boldsymbol{P}_{xz,k+1|k} \boldsymbol{P}_{zz,k+1|k}^{-1} \tag{15}$$

$$\hat{\boldsymbol{x}}_{k+1} = \hat{\boldsymbol{x}}_{k+1|k} + \boldsymbol{K}_{k+1}\left(\boldsymbol{z}_{k+1} - \hat{\boldsymbol{z}}_{k+1|k}\right) \tag{16}$$

$$\boldsymbol{P}_{k+1} = \boldsymbol{P}_{k+1|k} - \boldsymbol{K}_{k+1} P_{zz,k+1|k} \boldsymbol{K}_{k+1}^{\mathrm{T}} \tag{17}$$

III. Strong Tracking AUKF Algorithm

A. *Strong tracking adaptive filter*

The Strong Tracking Filter (STF) [6-8] has the following characteristics compared to the usual filters: 1) Stronger robustness with respect to model uncertainty; 2) Strong ability to track the status of mutations; 3) Moderate computational complexity. The main idea is to adjust the gain matrix online, forcing the residual sequences to be orthogonal to each other. This can force the filter to keep track of the state of the system when the system model is uncertain, thus improving the poor robustness and filtering divergence of UKF.

The true covariance matrix of the observation or state of the epoch m-step innovation or residual vector estimation is compared with the covariance matrix of the filtering recurrence model. When there is a deviation between these two kinds of covariance, the observed covariance matrix or state covariance matrix of the system will be adaptively adjusted according to the difference [9].

B. *The introduction of multiple suboptimal fading matrices*

After the analysis of the above theories, this system uses multiple suboptimal evanescent matrixes. Firstly, construct the observation covariance matrix with multiple epoch residuals. Then use the equivalence relation to obtain the self-adaptive correction matrix of measurement noise. Finally, use the modified measurement noise to calculate the gain matrix to achieve the purpose of adaptive adjustment of the state estimation. And re-estimate the nonlinear UKF filtering measurement noise.

The residual vector is calculated from the true measured value and the predicted measured value:

$$\tilde{\boldsymbol{Z}}_{k+1|k} = \boldsymbol{Z}_{k+1} - \hat{\boldsymbol{Z}}_{k+1|k} \tag{18}$$

In the formula: $\boldsymbol{Z}_{k+1}$ represents the real measurement value at time $k+1$, provided by GPS; $\hat{\boldsymbol{Z}}_{k+1|k}$ represents the prediction measurement estimate.

If the statistical characteristics of the true error measured by the system are consistent with the filtering recursive error model, there are:

$$\frac{1}{\tau}\sum_{j=k-\tau}^{k}\tilde{\boldsymbol{Z}}_{k+1|k}\tilde{\boldsymbol{Z}}_{k+1|k}^{T}=\boldsymbol{P}_{zz,k+1|k}+\boldsymbol{R}_{k+1} \quad (19)$$

In the formula, τ represents the number of epoch residuals collected.

When the system measurement is abnormal, the statistical characteristics of the true error of the measurement will be inconsistent with the filtering recursive error model. Add the evanescent matrix in (19):

$$\frac{1}{\tau}\sum_{j=k-\tau}^{k}\tilde{\boldsymbol{Z}}_{k+1|k}\tilde{\boldsymbol{Z}}_{k+1|k}^{T}=\boldsymbol{P}_{zz,k+1|k}+\boldsymbol{A}_{k+1}\boldsymbol{R}_{k+1} \quad (20)$$

Then,

$$\boldsymbol{A}_{k+1}=\left(\frac{1}{\tau}\left(\sum_{i=k-\tau}^{k}\tilde{\boldsymbol{Z}}_{k+1|k}\tilde{\boldsymbol{Z}}_{k+1|k}^{T}\right)-\boldsymbol{P}_{zz,k+1|k}\right)\boldsymbol{R}_{k+1}^{-1} \quad (21)$$

Comparing equation (19) and formula (21), we can see that $\boldsymbol{A}_{k+1}$ will adjust the filtering result when the noise is abnormal.

Due to the influence of calculation errors and other factors, the matrix needs further processing:

$$\boldsymbol{A}_{k+1}^{*}=diag(a_1,a_1,\cdots,a_n) \quad (22)$$

In the formula, $a_i=max\{1,(\boldsymbol{A}_{k+1})_{ii}\}$; $(\boldsymbol{A}_{k+1})_{ii}$ is the ii-th main diagonal element.

At this point, the equation (15) of the system update equations becomes:

$$\boldsymbol{K}_{k+1}=\boldsymbol{P}_{(XZ)_{k+1|k}}\left(\boldsymbol{P}_{(ZZ)_{k+1|k}}+\boldsymbol{A}_{k+1}^{*}\boldsymbol{R}_{k+1}\right)^{-1} \quad (23)$$

The other equations of the system update equations remain as they are.

When the noise of a measurement value in the measurement vector is abnormal, the corresponding item in the fading matrix will increase correspondingly, making the filter gain correspondingly smaller, thereby reducing the influence of the measurement abnormal value on the system state estimation. In addition, when the noises of multiple measurement values in the measurement vector are abnormal, it can also be accurately adjusted so that the system can obtain relatively accurate filtering results.

IV. DEEPLY INTEGRATED NAVIGATION MODEL UNDER LAUNCHING INERTIAL COORDINATE SYSTEM

The typical feature of GPS/SINS deeply integrated navigation system is that the degree of data information fusion is deeper, involving the GPS receiver internal tracking loop.

Combining the background of the launch inertial coordinate system of this paper, the main idea of deeply integrated navigation system design based on tightly integrated filter is to use INS output parameters and GPS receiver output parameters for comparison. The tightly integrated filter corresponds to different parameter information. And establish system state equations and measurement equations for state variables such as INS position error, velocity error and attitude error. After the optimal estimation of the AUKF filter, outputs the correction information, and the corrected INS information is used to assist the GPS receiver tracking loop. In this way, the system can suppress the dynamic stress error of the GPS tracking loop to a certain extent, reduce the tracking loop noise error of the carrier loop, improve the dynamic performance and anti-interference ability of the system, and achieve mutual assistance of the two systems in the observation process. In this system, a tightly integrated AUKF filter based on pseudo-range and pseudo-range ratio uses the original measurement values (pseudo-range, pseudo-range) of the GPS receiver, and this method will not introduce the error caused by GPS receiver navigation solution [10-11].

A. *SINS error state equation under launch inertial coordinate system*

The SINS error state equation is:

$$\dot{\boldsymbol{X}}(t)=\boldsymbol{F}(t)\boldsymbol{X}(t)+\boldsymbol{G}(t)\boldsymbol{W}(t) \quad (24)$$

In the formula, $\boldsymbol{X}$ represents the state error of the SINS, as follows:

$$\boldsymbol{X}=\begin{bmatrix}\varphi_x & \varphi_y & \varphi_z & \delta V_x & \delta V_y & \delta V_z & \delta X & \delta Y & \delta Z \\ \varepsilon_x & \varepsilon_y & \varepsilon_z & \nabla_x & \nabla_y & \nabla_z\end{bmatrix}^{\mathrm{T}} \quad (25)$$

In the formula: $\boldsymbol{\varphi}_x$, $\boldsymbol{\varphi}_y$, $\boldsymbol{\varphi}_z$ are the attitude misalignment angles of the launch inertial coordinate system; $\delta\boldsymbol{V}_x$, $\delta\boldsymbol{V}_y$, $\delta\boldsymbol{V}_z$ are the speed errors of the three axis directions of the launch inertial coordinate system; $\delta\boldsymbol{X}$, $\delta\boldsymbol{Y}$, $\delta\boldsymbol{Z}$ are the position errors of the three axis directions of the launch inertial coordinate system; $\boldsymbol{\varepsilon}_x$, $\boldsymbol{\varepsilon}_y$, $\boldsymbol{\varepsilon}_z$ are constant drifts of the gyroscope in the missile carrier coordinate system; ∇_x, ∇_y, ∇_z are the constant offsets of the accelerometer in the missile carrier coordinate system.

$\boldsymbol{F}(t)$ is the SINS system state transition matrix; $\boldsymbol{G}(t)$ is the SINS system noise drive matrix; $\boldsymbol{W}(t)$ is the SINS system noise matrix. The specific calculation formula of each matrix is shown in reference [12].

B. *GPS error state equation under launch inertial coordinate system*

In deeply integrated systems, the error state of the GPS receiver is usually taken as: the distance-rate error equivalent to the clock frequency error, and the distance error equivalent to the clock-frequency error. The state equation is:

$$\dot{\boldsymbol{X}}_g(t)=\boldsymbol{F}_g(t)\boldsymbol{X}_g(t)+\boldsymbol{G}_g(t)\boldsymbol{w}_g(t) \quad (26)$$

In the formula above:

$$\boldsymbol{X}_g(t)=\begin{bmatrix}\Delta l_u & \Delta l_{ru}\end{bmatrix}^{\mathrm{T}}, \qquad \boldsymbol{F}_g(t)=\begin{bmatrix}0 & 1\\ 0 & -\frac{1}{T_{ru}}\end{bmatrix},$$

$$\boldsymbol{G}_g(t)=\begin{bmatrix}1 & 0\\ 0 & 1\end{bmatrix}, \boldsymbol{w}_g(t)=\begin{bmatrix}w_u & w_{ru}\end{bmatrix}^{\mathrm{T}}.$$

Equations (24) and (26) form the state equation of the deeply integrated navigation system in the launch inertial coordinate system.

C. Measurement equation under launch inertial coordinate system

In this system, the deeply integrated GPS/SINS navigation system of ballistic missiles in the launch inertial coordinate system is divided into two parts: the pseudo-range measurement equation and the pseudo-range rate measurement equation. The expression is as follows:

$$\boldsymbol{Z} = \begin{bmatrix} \delta \boldsymbol{\rho} \\ \delta \dot{\boldsymbol{\rho}} \end{bmatrix} = \begin{bmatrix} \boldsymbol{\rho}_i - \boldsymbol{\rho}_g \\ \dot{\boldsymbol{\rho}}_i - \dot{\boldsymbol{\rho}}_g \end{bmatrix} \quad (27)$$

At some point, the true value of the position of the missile in the launch inertial coordinate system is $\begin{bmatrix} X & Y & Z \end{bmatrix}^{\mathrm{T}}$. If the true distance from the missile to the GPS satellite is ρ. The pseudo-range between the GPS receiver's position and the i-th satellite can be expressed as:

$$\rho_g = \rho + \delta l_u + v_\rho \quad (28)$$

Where: δl_u is the distance error caused by the GPS clock error and v_ρ is the pseudo-range measurement noise.

ρ and ρ_i can be calculated by the following formula:

$$\begin{cases} \rho = \sqrt{\left(X - X_s^j\right)^2 + \left(Y - Y_s^j\right)^2 + \left(Z - Z_s^j\right)^2} \\ \rho_i = \sqrt{\left(X_i - X_s^j\right)^2 + \left(Y_i - Y_s^j\right)^2 + \left(Z_i - Z_s^j\right)^2} \end{cases} \quad (29)$$

In the formula: $\begin{bmatrix} X_i & Y_i & Z_i \end{bmatrix}^{\mathrm{T}}$ is the position of the missile in the launch inertial coordinate system calculated by SINS, and $\begin{bmatrix} X_s^j & Y_s^j & Z_s^j \end{bmatrix}$ is the position coordinate of the i-th satellite converted to the launch inertial coordinate system.

Assume that $\begin{bmatrix} \delta X & \delta Y & \delta Z \end{bmatrix}^{\mathrm{T}}$ is the distance error between the SINS calculation position and the real position. Then:

$$\begin{cases} X_i = X + \delta X \\ Y_i = Y + \delta Y \\ Z_i = Z + \delta Z \end{cases} \quad (30)$$

Therefore, the pseudo-range difference nonlinear measurement equation is:

$$\delta\rho = \rho_i - \rho_g = \rho_i - \rho - \delta l_u - v_\rho \quad (31)$$

In the same way, the pseudo-range rate difference nonlinear measurement equation is:

$$\delta\dot{\rho} = \dot{\rho}_i - \dot{\rho}_g = \dot{\rho}_i - \dot{\rho} - \delta l_{ru} - v_{\dot{\rho}} \quad (32)$$

Where: $\dot{\rho}$ represents the true pseudo-range rate at the moment; δl_{ru} is the speed error caused by the GPS clock; $v_{\dot{\rho}}$ is the measurement noise. The specific derivation process is shown in reference [12].

From the above derivation, we can get the nonlinear measurement equation of GPS/SINS deeply integrated navigation in the launch inertial system. It should be noted that due to the nonlinear UKF filtering method, the system measurement equation does not need to be linearized.

V. THE SIMULATION AND RESULTS

In order to verify the superiority of the strong tracking GPS/SINS deeply integrated AUKF algorithm. Deeply integrated navigation simulation experiments were conducted in ballistic trajectory simulation platform and compared with the standard Unscented Kalman Filter (UKF).

A. Simulation conditions

The launch azimuth is 90°. And the initial speed in the launch inertial coordinate system is 394.8917 m/s (the speed of the Earth's rotation), and both the vertical direction and the lateral direction speed are 0 m/s.

The number of stars collected is four.

GPS sampling period is 1s, INS sampling period is 0.005s, the filtering period is 1s, and the simulation time is 360s.

The initial attitude: pitch angle is 90°; roll angle and yaw angle are all 0°.

The initial position: latitude is 31.98°; longitude is118.8°; height is 0m.

The gyroscope zero bias is 10°/h and white noise is 1°/h. The accelerometer zero bias is 1 mg and white noise is 0.5 mg.

In the 200s-210s period, the GPS pseudo-range adds white noise with a mean value of 0 and a standard deviation of 100, and the GPS pseudo-range rate adds white noise with a mean of 0 and a standard deviation of 1.

The trajectory of ballistic missile is shown in Figure 1.

B. Simulation Results and Analysis

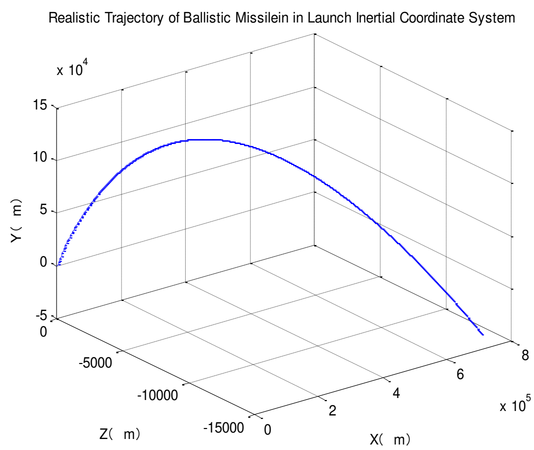

Figure.1 Trajectory of ballistic missile

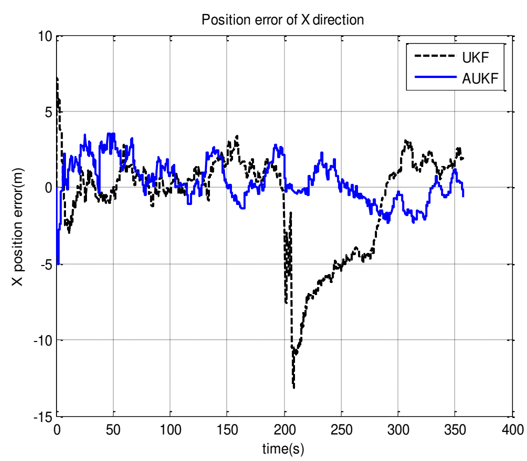

Figure.2 UKF and AUKF X-direction position error

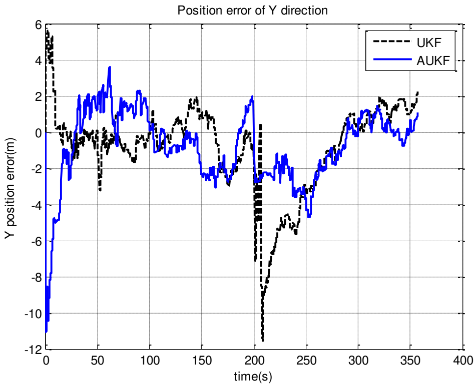

Figure.3 UKF and AUKF Y-direction position error

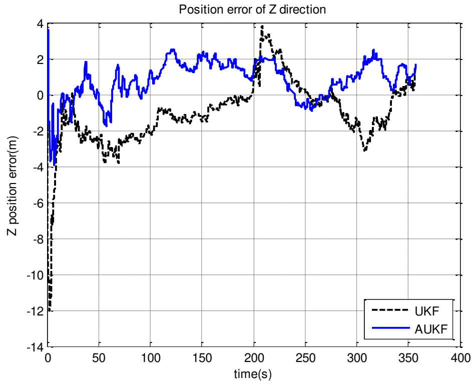

Figure.4 UKF and AUKF Z-direction position error

From the comparison of figure 2, figure 3 and figure 4, we can see that in the 200s-210s system subjected to strong interference, the X direction, Y direction and Z direction position error of the standard UKF algorithm are -13.11m, -11.53m, 3.80m; the X direction, Y direction and Z direction position error of the strong tracking AUKF algorithm are -0.28m, -2.66m, 2.12m. The absolute error is less than the standard UKF error. In addition, when the system is strongly interfered with, the strong tracking AUKF error fluctuation is small, the convergence speed is fast, the precision of integrated navigation positioning is greatly improved, and it has superior anti-interference ability and robustness.

VI. CONCLUSION

In view of the characteristics of high dynamic and strong interference of ballistic missiles and the problem of poor tracking ability and low filtering accuracy of standard UKF in this environment, this paper proposes a strong tracking AUKF algorithm. By introducing multiple suboptimal fading matrices, the algorithm can adjust the filter adaptively according to the measured characteristics of the system and increase the robust performance of the system. The algorithm is applied to GPS/SINS deep integrated navigation system in the launch inertial coordinate system. Simulation results show that the proposed algorithm can provide high precision navigation information for integrated navigation and proves the effectiveness of the algorithm.

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