Ultra-tight GPS/INS integration based long-range rocket projectile navigation method

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Abstract: Accurate navigation is important for long-range rocket projectile's precise striking. To obtain stable and high-performance navigation result, a ultra-tight global positioning system/inertial navigation system (GPS/INS) integration based navigation approach is proposed. The accurate short-time output of INS is used by GPS receiver to assist in acquisition of signal, and output information of INS and GPS is fused based on federated filter. Meanwhile, the improved cubature Kalman filter with strong tracking ability is chosen to serve as the local filter, and then the federated filter is enhanced based on vector sharing theory. Finally, simulation results show that the navigation accuracy with the proposed method is higher than that with traditional methods. It provides reference for long-range rocket projectile navigation.

Key words: long-range rocket projectile; global position system; inertial measuring unit; ultra-tight integration

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Long-range rocket projectile is a kind of widely used weapon equipment due to distant range and enormous fire power. Because the attacking precision of traditional rocket projectile can not fulfill the requirements of accurate striking, guidance rocket is designed to solve this problem. Guidance rocket projectile needs to implement flight control and ballistic correction in the course of the flight to hit the target precisely. In this case, the information of position and flight velocity must be measured in the course of the flight. In current navigation systems, global positioning system (GPS) and inertial measuring unit (IMU) are used widely[1-3]. Besides, celestial navigation system (CNS) and geomagnetism navigation system (GNS) are good choices, too[4]. Every navigation system has its own advantages.

As the projectile body is made of steel, it is easy to be magnetized in magnetism environment. Complex magnetic field will take place in the course of the flight when the projectile slices the magnetism field and the electromechanical system works. Therefore, magnetometer is not a good choice for projectile navigation. Projectile's roll angular velocity is high in the course of the flight, thus the celestial sensor can not capture the star constellation accurately and the CNS can not be used by projectile. But GPS and IMU do not yield to those constraints. The measurement error of GPS does not accumulate with time flying, but its accuracy is not high enough especially in high dynamic environment. The real-time feature and instantaneous accuracy of IMU are outstanding, but its measurement error accumulates with time flying. Therefore, many literatures made use of all the advantages of GPS and IMU by integrating them[1-3], but the current integration model used on rocket projectile and other guidance projectiles is loose integration. In this case, GPS signal may lose lock due to angular velocity, orbit error of satellite, signal propagation error, etc. Ultra-tight integrated model is proposed to solve this problem. It has been used in many fields[3,5] with satisfying performance, but there is not any literature using this principle to en-

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hance navigation precision of rocket projectile. We introduce it into projectile navigation and improve it.

1 Ultra-tight GPS/INS integration

MEMS IMU is used widely in guidance projectiles as its cost is low and cubage is small, but its measuring bias accumulates quickly. As a result, GPS is often used to assist the system in reducing error accumulation. Its integration model is shown in Fig. 1.

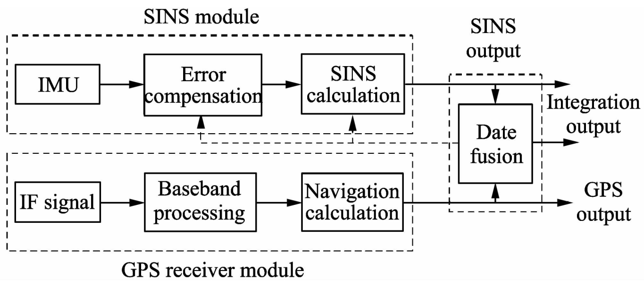

Fig. 1 Loose integration of GPS and IMU

In Fig. 1, IMU and GPS measure the position separately, and then fuse the position information. In this case, GPS output bias can not be reduced, which affects ultimate fusion result. To solve this problem, we can constrain output noise of GPS receiver via IMU real-time output before GPS outputs position information[5], and then integrates IMU position information with GPS position information. The ulltra-tight integration model is shown in Fig. 2.

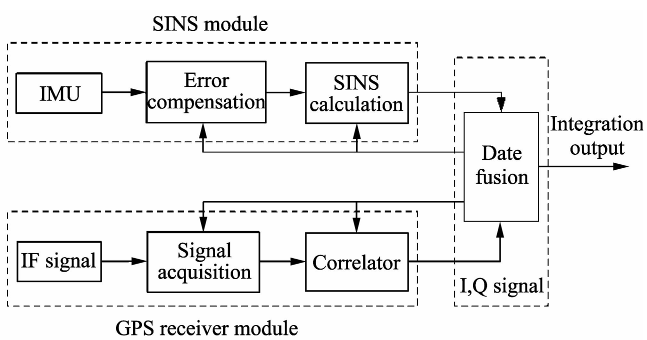

Fig. 2 Ultra-tight integration of GPS and IMU

As shown in Fig. 2, for ultra-tight integration, the signal acquisition is responsible for carrier phase tracking and locking. Traditionally, the carrier phase is got from phase locked loop (PLL) in GPS receiver. PLL principle can be expressed briefly in Fig. 3.

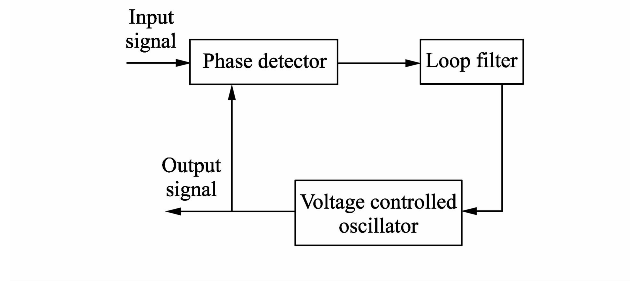

Fig. 3 PLL signal process procedure

To improve measurement accuracy of carrier phase, the common method is to improve PLL's tracking precision of satellite signal[4-5]. The tracking error of PLL is related to tracking loop's tape width. With the assistantce of IMU, we can solve the contradiction between loop noise and dynamic performance. By measuring the carrier velocity with IMU, the Doppler shift between carrier and satellite is estimated, and introduced into the oscillator control[5]. The use of IMU information can compensate the motion state and reduce the tracking loop's requirement for tape width, which reduces the noise effect on carrier phase tracking. The principle of IMU assisting PLL is shown in Fig. 4.

In the ultra-tight integration model, IMU information is used to get more accurate GPS output, and GPS information is used to integrate IMU information in the level of position to get more accurate navigation data in return. When IMU position is fused with GPS position, federated filter is used widely. In this study, federated filter is used and improved according to local filter and information sharing principle.

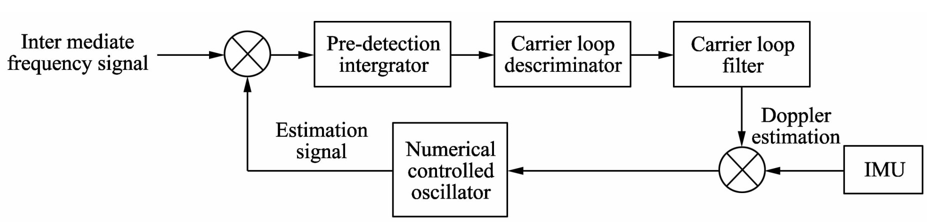

Fig. 4 IMU based pPhase locking loop principlee

2 Federated filter

Federated Kalman filter theory is a special form of distributed Kalman filtering fusion method proposed by American scholars Carlson in 1998. It is composed of several sub-filters and a main filter, and is a block-estimation and two-step cascade distributed filtering fusion method[6-7].

By using information distribution principle, we can get the optimal fusion output. It has high-precision, high fault tolerance and low computation burden properties.

In structure, it is different from parallel filtering algorithm, in which sub-filters are completely independent on each other. In federated filter, each sub-filter shares state information and measuring information from main filter. Its structure is shown in Fig. 5[7-10].

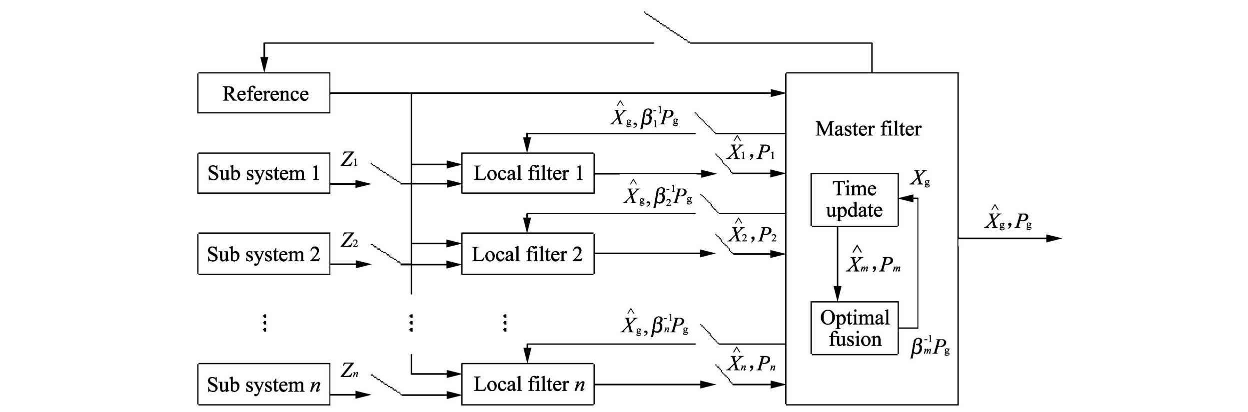

Fig. 5 Federated filter model

General discrete system state model is given by

$$\boldsymbol{X}(k) = \boldsymbol{\Phi}(k/k-1)\boldsymbol{X}(k-1) + \boldsymbol{\Gamma}(k)\boldsymbol{W}(k), \quad (1)$$

where $\boldsymbol{X}(k)$ is $n\times 1$ system state vector with time k; $\boldsymbol{\Phi}(k/k-1)$ is state transition matrix from time $k-1$ to time k; $\boldsymbol{\Gamma}(k)$ is $n\times r$ system noise matrix; $\boldsymbol{W}(k)$ is $r\times 1$ Gaussian noise and its variance is $r\times r$ matrix $\boldsymbol{Q}(k)$.

We can use process noise variance inverse matrix $\boldsymbol{Q}^{-1}$ to represent state information of the equation. In addition, the state estimation can be presented by variance inverse matrix $\boldsymbol{P}^{-1}$ and $\boldsymbol{R}^{-1}$ is variance inverse matrix of measurement noise in measurement equation. Assuming that state estimation vector, system estimation variance matrix and state vector variance matrix are denoted by $\hat{\boldsymbol{X}}_i$, $\boldsymbol{Q}_i$ and $\boldsymbol{P}_i$ for local filter i, and station estimate vector, system estimation variance matrix and state vector variance matrix of main filter are denoted by $\hat{\boldsymbol{X}}_g$, $\boldsymbol{Q}_g$ and $\boldsymbol{P}_g$, the main filter's information will be distributed to every local filter by the following regulation,

$$\boldsymbol{P}_g^{-1}\hat{\boldsymbol{X}}_g = \boldsymbol{P}_i^{-1}\hat{\boldsymbol{X}}_1 + \boldsymbol{P}_2^{-1}\hat{\boldsymbol{X}}_2 + \cdots + \boldsymbol{P}_n^{-1}\hat{\boldsymbol{X}}_n, \quad (2)$$

$$\boldsymbol{P}_g^{-1} = \boldsymbol{P}_1^{-2} + \boldsymbol{P}_2^{-1} + \cdots + \boldsymbol{P}_n^{-1}, \quad (3)$$

$$\hat{\boldsymbol{X}}_g = \boldsymbol{P}_g^{-1}\sum_{i=1}^{n}\boldsymbol{P}_i^{-1}\hat{\boldsymbol{X}}_i, \quad (4)$$

$$\hat{\boldsymbol{X}}_i = \hat{\boldsymbol{X}}_g, \quad (5)$$

$$\boldsymbol{P}_i^{-1} = \beta_i\boldsymbol{P}_g^{-1}, \quad (6)$$

$$\boldsymbol{Q}_g^{-1} = \boldsymbol{Q}_1^{-1} + \boldsymbol{Q}_2^{-1} + \cdots + \boldsymbol{Q}_n^{-1}, \quad (7)$$

$$\boldsymbol{Q}_i^{-1} = \beta_i\boldsymbol{Q}_g^{-1}. \quad (8)$$

where β_i is information distribution coefficient and complies with the following regulation,

$$\sum_{i=1}^{n}\beta_i + \beta_m = 1.$$

$$0 \leqslant \beta_i \leqslant 1,\ i = 1,2,\cdots,n. \quad (9)$$

Generally, if the system includes n local sensor systems and each system carries out measuring independently, there will be n individual measuring data. For local sensor i, its state equation and measuring equation can be presented as

$$\boldsymbol{X}_i(k) = \boldsymbol{\Phi}_i(k/k-1)\boldsymbol{X}_i(k-1) + \boldsymbol{\Gamma}_i(k)\boldsymbol{W}_i(k), \quad (10)$$

$$\boldsymbol{Z}_i(k)=\boldsymbol{H}_i(k)\boldsymbol{X}_i(k)+\boldsymbol{V}_i(k), \tag{11}$$

where $\boldsymbol{X}_i(k)$ is local system's state vector; $\boldsymbol{Z}_i(k)$ is local system's measuring vector and $\boldsymbol{V}_i(k)$ is Gaussian noise array of the corresponding local system.

Compared with other distributed fusion algorithms, federated Kalman filter has especial advantage in the process of information feedback and information distribution[7]. In the distribution process, information $\boldsymbol{Q}_i(k)$ and $\boldsymbol{P}_i(k)$ of each local system will be distributed by

$$\begin{cases}\boldsymbol{Q}_i(k-1)=\beta_i^{-1}\boldsymbol{Q}(k-1),\\ \boldsymbol{P}_i(k-1)=\beta_i^{-1}\boldsymbol{P}_g(k-1),\\ \boldsymbol{X}_i(k-1)=\boldsymbol{X}_g(k-1).\end{cases} \tag{12}$$

As seen from Eq. (12), after each integration circulation, each sub-filter is re-obtained from the optimum initial value of the integration output of the main filter, the sub-filter also gets the initial value which has been optimized to avoid error cumulation. After the distribution of information, each sub-filter completes time update alone according to their own recursion equation. The process can be expressed as

$$\hat{\boldsymbol{X}}_i(k/k-1)=\boldsymbol{\Phi}(k,k-1)\hat{\boldsymbol{X}}_i(k-1), \tag{13}$$

$$\boldsymbol{P}_i(k/k-1)=\boldsymbol{\Phi}(k,k-1)\boldsymbol{P}_i(k-1)\boldsymbol{\Phi}^{\mathrm{T}}(k,k-1)+\boldsymbol{\Gamma}(k,k-1)\boldsymbol{Q}_i(k-1)\boldsymbol{\Gamma}^{\mathrm{T}}(k,k-1).$$

$$i=1,2,\cdots,n. \tag{14}$$

Because the main filter does not receive the measuring value, measurement update is completed only in sub-systems. As a result, there is no main filter measurement update. The update process is described by

$$\boldsymbol{P}_i^{-1}(k)=\boldsymbol{P}_i^{-1}(k/k-1)+\boldsymbol{H}_i^{\mathrm{T}}(k)\boldsymbol{R}_i^{-1}\boldsymbol{H}_i(k), \tag{15}$$

$$\boldsymbol{P}_i^{-1}(k)\hat{\boldsymbol{X}}_i(k)=\boldsymbol{P}_i^{-1}(k/k-1)\hat{\boldsymbol{X}}_i(k/k-1)+\boldsymbol{H}_i^{\mathrm{T}}(k)\boldsymbol{R}_i^{-1}(k)\boldsymbol{Z}_i(k),$$

$$i=1,2,\cdots,n. \tag{16}$$

According to Eqs. (10)−(16), we can get $\hat{\boldsymbol{X}}_i(k)$. Then the estimation of each sub-filter will be integrated in the main filter. Finally, the optimal estimation is got. Fusion process can be expressed as

$$\boldsymbol{P}_g=[\boldsymbol{P}_1^{-1}+\boldsymbol{P}_2^{-1}+\cdots+\boldsymbol{P}_n^{-1}]^{-1}, \tag{17}$$

$$\hat{\boldsymbol{X}}_g=\boldsymbol{P}_g[\boldsymbol{P}_1^{-1}\hat{\boldsymbol{X}}+\boldsymbol{P}_2^{-1}\hat{\boldsymbol{X}}+\cdots+\boldsymbol{P}_n^{-1}\hat{\boldsymbol{X}}]=\boldsymbol{P}_g\sum_{i=1}^{n}\boldsymbol{P}_i\hat{\boldsymbol{X}}_i. \tag{18}$$

After fusion is finished, the optimal output of the main filter will be assigned to each sub-filter again. For the purpose of computing easily, distribution coefficients are given by

$$\begin{cases}\beta_i=\dfrac{trace(\boldsymbol{P}_i)}{\sum_{i=1}^{n}trace(\boldsymbol{P}_i)},\\ \beta_m=1-\sum\beta_i.\end{cases} \tag{19}$$

The notable feature of federal filter is that the filtering processing is done in the sub-filter, and the integration processing is completed in the main filter, then the main filter will give a feedback to sub-filter[8-10]. Therefore, the performance of the sub-filter will largely affect the overall performance of filtering fusion.

Just like what is expressed in Fig. 5, the optimal fusion part gets information from the local filter, therefore, the output accuracy of the local filter is rather important for the fusion result.

As the motion state has strong nonlinear feature, the traditional Kalman filter can not accord with this condition well, unscented Kalman filter (UKF) is introduced to solve this problem[5,8], but the data stability performance of UKF has not been proved up to now. Since its basic principle is unscented transform (UT), using $2n+1$ sigma points, the amount of calculation is huge. Based on high dimension accuracy and data stability, cubature filter is adopted in this paper.

Cubature Kalman filter (CKF) is the same as unscented Kalman filter[11-12], approximating the random variable density function by weight sampling. The difference between UKF and CKF is that CKF produces sigma point through cubature regulation instead of UT regulation. For common nonlinear state equation and observation equation, given that they satisfy

$$\boldsymbol{X}(k)=\boldsymbol{f}_i(\boldsymbol{X}(k-1))+\boldsymbol{\Gamma}(k)\boldsymbol{W}(k), \tag{20}$$

$$\boldsymbol{Z}_i(k)=\boldsymbol{h}_i(\boldsymbol{X}(k))+\boldsymbol{V}_i(k), \tag{21}$$

then cubature filter based time update process are as follows: given that the posterior probability density function $p(x(k-1)$ of time $k-1$ is known, we can decompose error variance $\boldsymbol{P}(k-1)$ via Cholesky decomposition[11] as

$$\boldsymbol{P}(k-1) = \boldsymbol{S}(k-1)\boldsymbol{S}^{\mathrm{T}}(k-1). \tag{22}$$

By calculating cubature point, we can get

$$\boldsymbol{x}_i(k/k-1) = \boldsymbol{S}(k-1)\xi_i + \hat{\boldsymbol{X}}(k-1), \tag{23}$$

where $\xi_i = \sqrt{\frac{m}{2}}[1]_i$, $i=1,2,\cdots,m$, $m=2n$; $[1]_i$ means the element i in the cubature point set[11-12].

Propagating cubature point through state equation as

$$\boldsymbol{\chi}_i(k/k-1) = f(\boldsymbol{x}_i(k/k-1). \tag{24}$$

Estimating the state prediction value of time k as

$$\hat{\boldsymbol{X}}(k/k-1) = \frac{1}{m}\sum_{i=1}^{m}\boldsymbol{\chi}_i(k/k-1). \tag{25}$$

As a result, the prediction value of error variance of time k can be expressed as

$$\boldsymbol{P}(k/k-1) = \frac{1}{m}\sum_{1}^{m}\boldsymbol{\chi}_i(k/k-1)\boldsymbol{\chi}_i^{\mathrm{T}}(k/k-1) - \hat{\boldsymbol{X}}(k/k-1)\hat{\boldsymbol{X}}^{\mathrm{T}}(k/k-1) + \boldsymbol{Q}(k-1). \tag{26}$$

After calculating the value of $\boldsymbol{P}(k/k-1)$, $\boldsymbol{P}(k/k-1)$ is decomposed by cholesky decomposition as[11-12]

$$\boldsymbol{P}(k/k-1) = \boldsymbol{S}(k/k-1)\boldsymbol{S}^{\mathrm{T}}(k/k-1). \tag{27}$$

Based on this cubature point is calculated by

$$\boldsymbol{x}_i(k/k-1) = \boldsymbol{S}(k/k-1)\boldsymbol{S}^{\mathrm{T}}(k/k-1). \tag{28}$$

Propagating cubature point via measuring equation,

$$\boldsymbol{z}_i(k/k-1) = h(\boldsymbol{x}_i(k/k-1)), \tag{29}$$

$$\hat{\boldsymbol{Z}}(k/k-1) = \frac{1}{m}\sum_{i=1}^{m}\boldsymbol{z}_i(k/k-1), \tag{30}$$

$$\boldsymbol{P}_{ZZ}(k/k-1) = \frac{1}{m}\boldsymbol{z}_i(k/k-1)\boldsymbol{z}_i^{\mathrm{T}}(k/k-1) - \hat{\boldsymbol{Z}}(k/k-1)\hat{\boldsymbol{Z}}^{\mathrm{T}}(k/k-1) + \boldsymbol{R}(k), \tag{31}$$

$$\boldsymbol{P}_{XZ}(k/k-1) = \frac{1}{m}\boldsymbol{x}_i(k/k-1)\boldsymbol{z}_i^{\mathrm{T}}(k/k-1) - \hat{\boldsymbol{X}}(k/k-1)\hat{\boldsymbol{Z}}^{\mathrm{T}}(k/k-1). \tag{32}$$

So we can get the state estimation,

$$\boldsymbol{X}(k) = \boldsymbol{X}(k/k-1) + \boldsymbol{K}(k)(\boldsymbol{Z}(k) - \hat{\boldsymbol{Z}}(k/k-1)), \tag{33}$$

$$\boldsymbol{K}(k) = \boldsymbol{P}_{XZ}(k/k-1)\boldsymbol{P}_{ZZ}^{-1}(k/k-1). \tag{34}$$

At the same time, we can get the current state variance matrix,

$$\boldsymbol{P}(k) = \boldsymbol{P}(k/k-1) - \boldsymbol{W}(k)\boldsymbol{P}_{ZZ}(k/k-1)\boldsymbol{W}^{\mathrm{T}}(k). \tag{35}$$

CKF algorithm is based on spherical-radial cubature criteria. For all nonlinear state equations, there is not linearization process of the model, but it spreads cubature point through the equation, so it is applicable to all forms of nonlinear models. This article takes CKF as sub-filters in federated filter, which can reduce the adverse impact of the filter caused by nonlinear factor. Meanwhile, it reduces the amount of calculation.

Refs. [11] and [12] proved the validity of cubature filter in the complex environment and provides a reference for application, but the filtering result still does not satisfy the requirement well when using traditional cubature filter because the model inaccuracy factor is still the main problem which affects the last filter accuracy. To solve this problem, Refs. [13] and [14] proposed a strong tracking approach. Based on this, the strong tracking principle which is used in unscented Kalman filter is introduced into cubature filter in this paper to weaken the effect of modeling error. The operational process is as follows.

For Eqs. (31)−(32), the calculation process is improved as

$$\boldsymbol{P}_{ZZ}(k/k-1) = \lambda(k)\frac{1}{m}\sum_{i=1}^{m}\boldsymbol{z}_i(k/k-1)\boldsymbol{z}_i^{\mathrm{T}}(k/k-1) - \hat{\boldsymbol{Z}}(k/k-1)\hat{\boldsymbol{Z}}^{\mathrm{T}}(k/k-1) + \boldsymbol{R}(k), \tag{36}$$

$$\boldsymbol{P}_{XZ}(k/k-1) = \lambda(k)\frac{1}{m}\sum_{i=1}^{m}\boldsymbol{x}_i(k/k-1)\boldsymbol{z}_i^{\mathrm{T}}(k/k-1) - \hat{\boldsymbol{X}}(k/k-1)\hat{\boldsymbol{Z}}^{\mathrm{T}}(k/k-1), \tag{37}$$

$$\boldsymbol{P}(k) = \lambda(k)\boldsymbol{P}(k/k-1) - \boldsymbol{W}(k)\boldsymbol{P}_{ZZ}(k/k-1)\boldsymbol{W}^{\mathrm{T}}(k), \tag{38}$$

$$\lambda(k) = \begin{cases} \lambda(0) & \lambda > 0, \\ 1 & \lambda \leqslant 0, \end{cases} \tag{39}$$

$$\lambda(0)=\frac{\mathrm{tr}(\boldsymbol{N}(k))}{\mathrm{tr}(\boldsymbol{M}(k))},\tag{40}$$

$$\boldsymbol{V}_r(k)=\begin{cases}\boldsymbol{r}(1)\boldsymbol{r}^{\mathrm{T}}(1),\\ \dfrac{\rho\boldsymbol{V}_r(k-1)+\boldsymbol{r}(k)\boldsymbol{r}^{\mathrm{T}}(k)}{1+\rho},\end{cases}\tag{41}$$

where $\boldsymbol{N}(k)=\boldsymbol{V}_r(k)-\beta\boldsymbol{R}(k)$, $\boldsymbol{R}(k)$ is the observation system noise, $\boldsymbol{r}$ is the observation vector prediction residual error, and

$$\boldsymbol{M}(k)=\frac{1}{m}\sum_{i=0}^{m}(\boldsymbol{z}_i(k/k-1)-\hat{\boldsymbol{Z}}(k/k-1))(\boldsymbol{z}_i(k/k-1)-\hat{\boldsymbol{Z}}(k/k-1))^{\mathrm{T}},\tag{42}$$

where $0<\rho\leqslant 1$ is the forgetting factor, and β is the reduction factor[13-14].

In traditional federated filter, as expressed in Fig. 5, the allocation factor β determines the fusion result, and the parameter β is scalar, which can not reflect the effect of observability degree. Therefore, we improve it based on vector sharing principle[15,16].

After the improvement, the fusion structure of GPS/INS based federated filter is shown in Fig. 6.

$$\boldsymbol{b}_i=\sqrt{\frac{1}{2}(\boldsymbol{A}_i+\boldsymbol{r}_i)^{-1}},\tag{43}$$

where $$\boldsymbol{A}_i=\mathrm{diag}(a_{i1},a_{i2},\cdots,a_{i}n),\tag{44}$$

$$a_{ij}=\frac{1/\lambda_{ij}}{1/\lambda_{1j}+1/\lambda_{2j}+\cdots+1/\lambda_{Nj}},\tag{45}$$

$$i=1,2,\cdots,N;\ j=1,2,\cdots,n,$$

$$\boldsymbol{P}_i=\boldsymbol{L}_i\boldsymbol{\Lambda}_i\boldsymbol{L}_i^{\mathrm{T}},$$

$$\boldsymbol{\Lambda}_i=\mathrm{diag}(\lambda_{i1},\lambda_{i2},\cdots,\lambda_{in}),$$

$$\boldsymbol{r}_i=\mathrm{diag}(r_{i1},r_{i2},\cdots,r_{in}),$$

$$r_{ij}=\frac{\sigma_{ij}}{\sigma_{1j}+\sigma_{2j}+\cdots+\sigma_{Nn}},\tag{46}$$

where σ_{ij} is the observability matrix singular value[15-16].

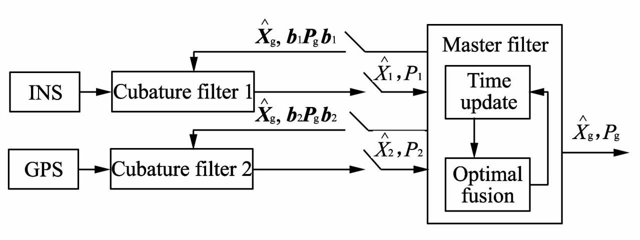

Fig. 6 Vector sharing principle based federated filter

3 Simulation

To test whether this method proposed in this article is useful and available, we carried out simulation based on the following information.

The gyro constant drift 0.3 (°)/h, white noise variance is 0.02° and the first order coefficient 5×10^{-6}; accelerometer constant drift is 100 μs and white noise variance 100 μg; GPS signal intermediate frequency is 7 MHz, sampling frequency is 30 MHz, carrier phase loop noise bandwidth is 10 Hz, damping factor is 0.7, code loop bandwidth is 2.5 Hz, carrier loop gain is 0.3 and code loop gain is 0.5; By the help of IMU, carrier bandwidth is 0.3 Hz, and code loop is changed into the first order and its bandwidth is 0.5 Hz.

In the simulation, the flight time is set at 600 s, the position and velocity error of two different methods are shown in Fig. 7 and Fig. 8. The loose integration method fuses the output information of GPS and INS with UKF federated filter, and the ultra-tight integration method is the method proposed in this paper.

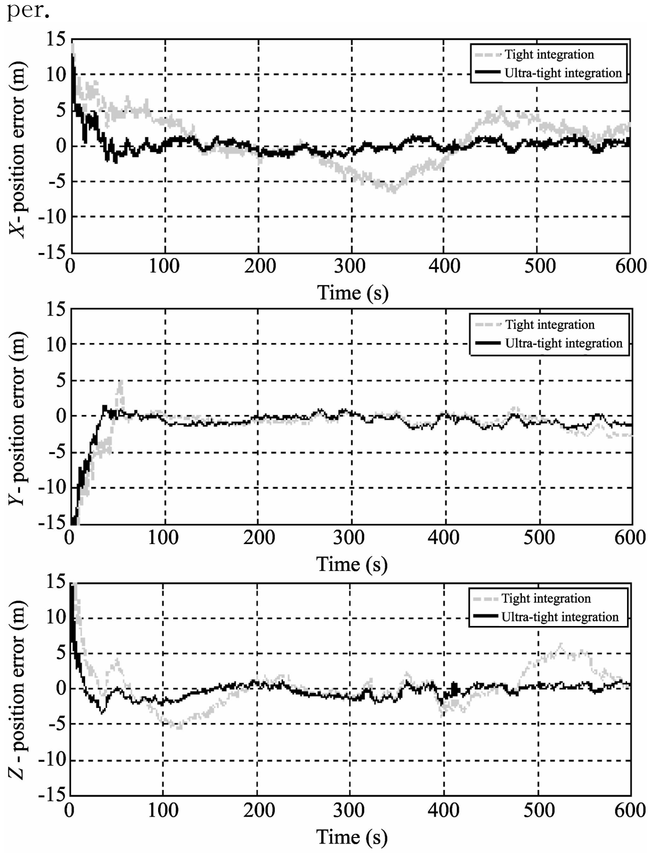

Fig. 7 Position estimation error statistics

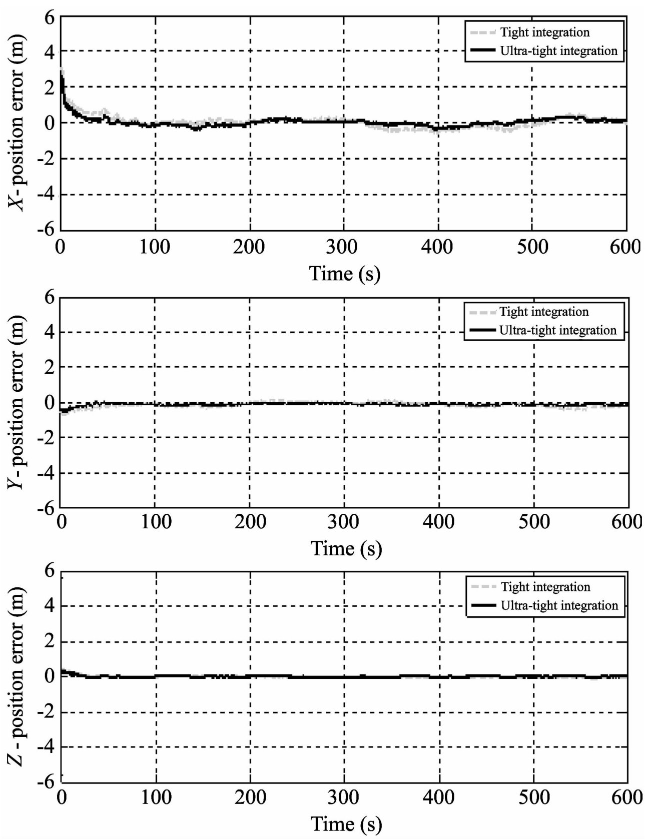

Fig. 8 Velocity estimation error statistics

It can be seen that the positioning accuracy of the proposed method is higher than that of traditional GPS/INS integration method. However, the velocity measuring is not obviously good because the output frequency of GPS is much less than that of INS. Therefore, the INS offers the velocity mainly in both kinds of integration methods.

4 Conclusion

A new navigation method for long-range rocket projectile based on information fusion algorithm is proposed in this paper. The simulation results show that the positioning accuracy of the proposed method is higher obviously than that of traditional method. As the computing amount of cubature filter is less than that of UKF, this approach consideres the computing time and output precision at the same time, providing a new method for engineering application.

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基于超紧耦合 GPS/INS 的远程火箭弹组合导航方法

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摘 要： 精确导航对远程火箭弹的精准打击具有至关重要的作用。为了获得稳定、高效的导航效果，提出了一种基于 GPS/INS 超紧耦合的组合导航方法。首先，利用 INS 短时输出精度高的优势，辅助 GPS 的信号捕获，然后再将 GPS 的输出信息同 INS 的输出信息进行联邦滤波融合。同时，在滤波算法上使用了容积滤波算法，并进行了强跟踪改进，且对联邦滤波的因子分配方法进行了基于矢量分配原理的改进。最后进行了组合导航的仿真。结果表明，基于本文方法的导航精度高于普通紧组合方法的导航精度，这为远程火箭弹的精确导航提供了参考。

关键词： 远程火箭弹；卫星定位系统；惯性测量单元；超紧耦合组合

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