A New Efficient Filtering Model for GPS/SINS Ultratight Integration System

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Global Positioning System (GPS) and strap-down inertial navigation system (SINS) are recognized as highly complementary and widely employed in the community. The GPS has the advantage of providing precise navigation solutions without divergence, but the GPS signals might be blocked and attenuated. The SINS is a totally self-contained navigation system which is hardly disturbed. The GPS/SINS integration system could utilize the advantages of both the GPS and SINS and provide more reliable navigation solutions. According to the data fusion strategies, the GPS/SINS integrated system could be divided into three different modes: loose, tight, and ultratight integration (LI, TI, and UTC). In the loose integration mode, position and velocity difference from the GPS and SINS are employed to compose measurement vector, in which the vector dimension has nothing to do with the amount of the available satellites. However, in the tight and ultratight modes, difference of pseudoranges and pseudorange rates from the GPS and SINS are employed to compose the measurement vector, in which the measurement vector dimension increases with the amount of available satellites. In addition, compared with the loose integration mode, clock bias and drift are included in the integration state model. These two characteristics magnify the computation load of the tight and ultratight modes. In this paper, a new efficient filter model was proposed and evaluated. Two schemes were included in this design for reducing the computation load. Firstly, a difference between pseudorange measurements was determined, by which clock bias and drift were excluded from the integration state model. This step reduced the dimension of the state vector. Secondly, the integration filter was divided into two subfilters: pseudorange subfilter and pseudorange rate subfilter. A federated filter was utilized to estimate the state errors optimally. In the second step, the two subfilters could run in parallel and the measurement vector was divided into two subvectors with lower dimension. A simulation implemented in MATLAB software was conducted to evaluate the performance of the new efficient integration method in UTC. The simulation results showed that the method could reduce the computation load with the navigation solutions almost unchanged.

1. Introduction

Recently, Global Positioning System (GPS) triggers a revolution in position, navigation, and timing (PNT). Smartphones, vehicles, pedestrians, and ships all employ GPS to provide continuous and precise positioning, navigation, and timing (PNT) information [1–5]. With the satellites in space covering the earth, the GPS receiver around the world can receive the broadcast satellite signals and output PNT information [1–5]. With the fast development of GPS receiver design and manufacturing technology, currently, a low-cost handheld receiver is capable of positioning accurately in open sky. A GPS chip receiver has been embedded in mobile devices for Location-Based Service (LBS), which makes great influence on people’s daily life. However, for a standalone GPS receiver, signal challenging environment might hinder its extensive applications, for instance, NLOS (none-of-sight) and multipath (MP) signal in urban canyons and dynamic stress under high dynamic; these negative factors may affect the signal availability or navigation solution accuracy and integrity. Without enough satellites with “clean” signals available, the receiver will fail to output correct PNT information [2–8]. For instance, the NLOS signals will cause the pseudorange bias, signal blockage will
influence the satellite geometry distribution, and the MP will also influence the errors in pseudorange measurements [2–14].

Researchers have been working on improving the receivers' ability and performance of positioning under signal-challenging environments [9–14]. Hsu proposed the multipath mitigation and NLOS detection method using vector tracking with machine learning method [9, 10]. In addition, the dual-polarization antenna and 3D city model were employed for NLOS detection, correction, and exclusion [11, 12]. Petovello investigated extending the integration time for enhancing the weak signal tracking [13, 14]. Apart from enhancing the standalone receiver's performance, integrating the GPS with other sensors has been one of the most promising and effective methods, especially the GPS/SINS integration [15–27].

The SINS is a sort of self-contained navigation system, which is hardly disturbed. The SINS processes the angular and acceleration measurements from the inertial measurement unit (IMU), and then 3D georeference information is generated without transmitting or receiving any outside signals [6–8]. However, the random noises contained in the angular and acceleration measurements will lead to the navigation solution errors accumulating dramatically over time [6–8]. Therefore, the SINS is usually integrated with the GPS for providing more stable and reliable navigation solutions. When the GPS works well, it can calibrate the SINS and compensate the errors through the integration. When the GPS is unavailable attenuated, the SINS can provide short-term accurate navigation solutions instead of the GPS. Moreover, for dynamic applications, the SINS can provide navigation solutions at higher rates, which can fill the gap between GPS information and smooth the navigation solutions [15–17].

In recent years, researchers are attracted to improve and enhance GPS/SINS integration system performance. Generally, there are two extensive approaches: modifying the integration model or modifying the integration filter [17–22]. As aforementioned, GPS/SINS integration can be divided into three modes: loose, tight, and ultratight integration (LI, TI, and UTC). The integration architecture is classified according to the levels of the measurements included in the GPS/SINS data fusion and whether SINS information is employed to aid GPS signal tracking [21, 22]. The most widely used mode is the loose integration method, in which navigation solutions from the GPS and SINS are directly employed to compose measurement vector and estimate SINS state errors. For the TI or UTC, pseudorange and pseudorange rate measurements from the GPS and SINS are employed as the integration filter measurements. Compared with LI, clock bias and drift are included in the TI or UTC state model, the dimension of TI or UTC measurement vector increases over the amount of available satellites. Various UTC implementations were published [22–26]. For instance, vector tracking was employed in UTC substituting scalar tracking [27–30]. In the aspects of the integration filter modification, nonlinear Kalman filter (cubature Kalman Filter, CKF; unscented Kalman filter, UKF) and some advanced Kalman filter variants were investigated in the GPS/SINS integration system for enhancing the GPS/SINS integration performance [23–31]. However, limited research had been conducted on how to reduce the computation load of the UTC integration filter.

In this paper, a new efficient UTC integration filter was proposed, investigated, and assessed. In the proposed method, a pseudorange/pseudorange rate measurement difference scheme was employed to exclude clock bias and drift error from the UTC integration filtering model, which reduces the dimension of the state vector. Based on this, the measurement vector was divided into two sub-vectors with much lower dimension: pseudorange and pseudorange rates subvector. With the above operation, the integration filter was divided into two individual subfilters and a federated Kalman filter was employed to fuse them and obtain optimal estimation of state errors. In this architecture, the dimension reduction of the state and measurement vector could enhance the real-time performance of the UTC integration.

The remainder of this paper is organized as follows: Section 2 gives the integration model in detail including the difference scheme and integration filter model. Section 3 presents the simulation and the result analysis; then, the paper is concluded.

2. Model and Method

This section explains the integration model in detail. In the GPS/SINS UTC model, SINS device errors and clock bias/ drift are employed as state variable. The measurement model is constructed based on the pseudorange and pseudorange rate errors between GPS and SINS considering clock bias and drift. Section 2.1 shows the conventional ultratight integration filtering model, and section 2.2 illustrates the measurement difference scheme and the new integration filtering model. Section 2.3 shows the architecture of the federated Kalman filter (FKF), which is employed in the state errors estimation.

2.1. The Integration Model

2.1.1. The Integration Filter State Model. The integration scheme includes 17 states, and the state vector \( \mathbf{X} \) is defined as

\[
\mathbf{X} = \left[ \delta \phi, \delta \text{vel}, \delta \text{pos}, \delta \epsilon, \delta \nabla, c \cdot \delta t_u, c \cdot \delta t_u \right]^T,
\]

where the vector \( \delta \phi = [\alpha, \beta, \gamma] \) is the error of pitch, roll, and yaw angles, the vector \( \delta \text{vel} = [\delta v_x, \delta v_y, \delta v_z] \) is the error of east, north, and up velocity in E–N–U navigation frames, the vector \( \delta \text{pos} = [\delta L, \delta \lambda, \delta \delta h] \) is the latitude, longitude and height (LLH) errors, the vector \( \delta \epsilon = [\varepsilon_x, \varepsilon_y, \varepsilon_z] \) is the gyroscope bias in the body frame, the vector \( \delta \nabla = [\nabla_x, \nabla_y, \nabla_z] \) is the accelerometer bias, and the variables \( c \cdot \delta t_u \) and \( c \cdot \delta t_u \) are the clock bias and the clock drift expressed in meters and drift meters/second.

The integration filter is commonly a Kalman filter; thus, the state equations can be written as
\[ \dot{X} = F \cdot X + W, \]  
where \( F \) is the state transfer matrix and \( W \) is the system error matrix.  

\[
F = \begin{bmatrix} F_{\text{INS}} & 0 \\ 0 & F_{\text{GPS}} \end{bmatrix}
\]

where \( F_{\text{INS}} \) is the system dynamic matrix of the SINS and \( F_{\text{GPS}} \) is the system dynamic matrix of GPS clock error [18–21].

### 2.1.2. The Integration Filter Observation Model

The measurement vector of the integration model is composed of pseudorange error and the pseudorange rate difference between the GPS and SINS. Supposing the user’s real position is \( \text{Pos}_{\text{Real}} = [x_{\text{real}} y_{\text{real}} z_{\text{real}}]^T \), the calculated position from the INS is \( \text{Pos}_{\text{INS}} = [x_{\text{INS}} y_{\text{INS}} z_{\text{INS}}]^T \) and the position vector of the satellite \( i \) is \( \text{Sat}_{\text{Pos}} = [x_i y_i z_i]^T \). Thus, the pseudorange between the satellite \( i \) and the receiver can be written as

\[
\rho_{\text{INS}}^{(i)} = \text{Sat}_{\text{Pos}} - \text{Pos}_{\text{INS}}
\]

\[
= \sqrt{(x_i - x_{\text{INS}})^2 + (y_i - y_{\text{INS}})^2 + (z_i - z_{\text{INS}})^2},
\]

The real range is

\[
r_0^{(i)} = |\text{R}_{(i)} - \text{R}_{0}| = \sqrt{(x_i - x_0)^2 + (y_i - y_0)^2 + (z_i - z_0)^2}.
\]

After the first-order linearization, equation (4) can be written as the following equation:

\[
\rho_{\text{INS}}^{(i)} = r_0^{(i)} + \frac{x_i - x_0}{r_0^{(i)}} \delta x_{\text{INS}} + \frac{y_i - y_0}{r_0^{(i)}} \delta y_{\text{INS}} + \frac{z_i - z_0}{r_0^{(i)}} \delta z_{\text{INS}},
\]

where

\[
\delta x = x_{\text{INS}} - x_0, \\
\delta y = y_{\text{INS}} - y_0, \\
\delta z = z_{\text{INS}} - z_0.
\]

In the GPS receiver, the GPS pseudorange error model usually includes the satellite clock error, atmospheric error, receiver clock error, and other factors. After correcting ionospheric error and tropospheric error, the pseudorange error model can be written as

\[
\rho_{\text{GPS}}^{(i)} = r_0^{(i)} - c \cdot \delta t + \epsilon_p.
\]

Thus, the difference between the GPS and SINS pseudorange can be written as

\[
\delta \rho^{(i)} = \rho_{\text{INS}}^{(i)} - \rho_{\text{GPS}}^{(i)} = \frac{x_i - x_0}{r_0^{(i)}} \delta x - \frac{y_i - y_0}{r_0^{(i)}} \delta y - \frac{z_i - z_0}{r_0^{(i)}} \delta z - c \cdot \delta t + \epsilon_p.
\]

The pseudorange rate measurement vector \( Z_p \) can be written as

\[
Z_p = \left[ \begin{array}{c} \delta \rho^1 \\ \vdots \\ \delta \rho^N \end{array} \right] = H^p \cdot X + V_p,
\]

where

\[
H^p = \begin{bmatrix} A_p & 0_{N \times 3} & 0_{N \times 9} & C_p \end{bmatrix},
\]

and

\[
A_p = \begin{bmatrix} e^x_N & e^y_N & e^z_N \\ \vdots & \vdots & \vdots \\ e^x_N & e^y_N & e^z_N \end{bmatrix}_{N \times 3},
\]

\[
C_p = \begin{bmatrix} -1 & 0 \\ \vdots & \vdots \\ -1 & 0 \end{bmatrix}_{N \times 2},
\]

where \( E_p \) is the position transformation matrix from E-N-U coordinates to ECEF coordinates, respectively. Similarly, the pseudorange rate measurement can be written as

\[
\delta \dot{\rho}^{(i)} = \dot{\rho}_{\text{INS}}^{(i)} - \dot{\rho}_{\text{GPS}}^{(i)} = \frac{x_i - x_0}{r_0^{(i)}} \delta \dot{x} - \frac{y_i - y_0}{r_0^{(i)}} \delta \dot{y} - \frac{z_i - z_0}{r_0^{(i)}} \delta \dot{z} - c \cdot \delta \dot{t} + \epsilon_{\dot{p}},
\]

where \((\delta \dot{x}, \delta \dot{y}, \delta \dot{z})\) is the SINS velocity error vector in ECEF coordinates. The equations are detailed in [11, 12]. The pseudorange rate measurement vector \( Z_{\dot{p}} \) can be written as

\[
Z_{\dot{p}} = \begin{bmatrix} \delta \dot{p}^1 \\ \vdots \\ \delta \dot{p}^N \end{bmatrix} = H^\dot{p} \cdot X + V_{\dot{p}},
\]

where
where \( \mathbf{E}_p \) is the velocity transformation matrix from E-N-U coordinates to ECEF coordinates, respectively. Thus, the measurement equation can be written as
\[
\mathbf{Z} = \begin{bmatrix} \mathbf{Z}_p \\ \mathbf{Z}_p \end{bmatrix}.
\] (15)

### 2.2. The Differential Scheme.
As aforementioned, channels from the same receiver share a common clock bias and drift. Difference between channels can definitely exclude clock bias and clock drift from the UTC model. Pseudorange error differential equations can be written as follows:
\[
\eta_{mn} = \delta \rho_{mn} = \rho_{INS} - \rho_{GPS} = \frac{\rho_{INS} - \rho_{GPS}}{\rho_{INS} - \rho_{GPS}}
\]
\[
\begin{align*}
\delta \eta_{mn} &= \frac{x(n) - x_0}{r_0^n} \delta x + \frac{y(n) - y_0}{r_0^n} \delta y + \frac{z(n) - z_0}{r_0^n} \delta z \\
+ \frac{x(n) - x_0}{r_0^n} \delta x + \frac{y(n) - y_0}{r_0^n} \delta y + \frac{z(n) - z_0}{r_0^n} \delta z \\
\end{align*}
\]
\[
\begin{align*}
\delta \eta_{mn} &= \frac{x(n) - x_0}{r_0^n} \delta x + \frac{y(n) - y_0}{r_0^n} \delta y + \frac{z(n) - z_0}{r_0^n} \delta z \\
+ \frac{x(n) - x_0}{r_0^n} \delta x + \frac{y(n) - y_0}{r_0^n} \delta y + \frac{z(n) - z_0}{r_0^n} \delta z \\
\end{align*}
\] (16)

Similarly, the pseudorange rate error differential equations are as follows:
\[
\mu_{mn} = \delta \mu_{mn} = \rho_{INS} - \rho_{GPS} = \frac{\rho_{INS} - \rho_{GPS}}{\rho_{INS} - \rho_{GPS}}
\]
\[
\begin{align*}
\delta \mu_{mn} &= \frac{x(n) - x_0}{r_0^n} \delta \nu_x + \frac{y(n) - y_0}{r_0^n} \delta \nu_y + \frac{z(n) - z_0}{r_0^n} \delta \nu_z \\
+ \frac{x(n) - x_0}{r_0^n} \delta \nu_x + \frac{y(n) - y_0}{r_0^n} \delta \nu_y + \frac{z(n) - z_0}{r_0^n} \delta \nu_z \\
\end{align*}
\]
\[
\begin{align*}
\delta \mu_{mn} &= \frac{x(n) - x_0}{r_0^n} \delta \nu_x + \frac{y(n) - y_0}{r_0^n} \delta \nu_y + \frac{z(n) - z_0}{r_0^n} \delta \nu_z \\
+ \frac{x(n) - x_0}{r_0^n} \delta \nu_x + \frac{y(n) - y_0}{r_0^n} \delta \nu_y + \frac{z(n) - z_0}{r_0^n} \delta \nu_z \\
\end{align*}
\] (17)

The new model of the integration filter is as follows:
\[
\begin{align*}
\hat{\mathbf{X}}_{k+1} &= \mathbf{F} \hat{\mathbf{X}}_k + \mathbf{W}_k \\
\tilde{\mathbf{Z}}_k &= \mathbf{H} \hat{\mathbf{X}}_k + \mathbf{V}_k.
\end{align*}
\] (18)

The new state vector is
\[
\hat{\mathbf{X}} = [\delta \phi, \delta \text{vel}, \delta \text{pos}, \delta \epsilon, \delta \mathbf{v}]^T.
\] (19)

The measurement vector is
\[
\tilde{\mathbf{Z}} = [\eta_{1,2}, \eta_{1,3}, \ldots, \eta_{1,m}, \mu_{1,2}, \mu_{1,3}, \ldots, \mu_{1,m}]^T.
\] (20)

### 2.3. The Federated Filter Scheme.
For reducing the dimension of the measurement vector, a simple federated filter (FEF) with two subfilters are designed and employed to optimally fuse the measurements; the FEF architecture is shown in Figure 1. The state vector is identical to equation (19), and the detailed description of the subfilters is given in equations (21)–(24). Equations (21) and (22) are the pseudorange subfilter state vector and measurement vector:
\[
\begin{align*}
\hat{\mathbf{X}}_{\eta} &= \mathbf{F}_{\eta} \hat{\mathbf{X}}_{\eta} + \mathbf{W}_{\eta} \\
\tilde{\mathbf{Z}}_{\eta} &= \mathbf{H}_{\eta} \hat{\mathbf{X}}_{\eta} + \mathbf{V}_{\eta}.
\end{align*}
\] (21)

The state vector and measurement vector of the pseudorange rate subfilter are as follows:
\[
\begin{align*}
\hat{\mathbf{X}}_{\mu} &= \mathbf{F}_{\mu} \hat{\mathbf{X}}_{\mu} + \mathbf{W}_{\mu} \\
\tilde{\mathbf{Z}}_{\mu} &= \mathbf{H}_{\mu} \hat{\mathbf{X}}_{\mu} + \mathbf{V}_{\mu}.
\end{align*}
\] (23)

### 3. Experiment and Results
A simulation was implemented and conducted in MATLAB software. Dynamic trajectory was generated to assess the new UTC filtering method. Navigation solutions including position, velocity, and altitude were compared between UTC with difference and the UTC without difference, which aimed to explore whether excluding clock bias and drift makes a negative impact on navigation solution accuracy. Table 1 shows the parameter setting of the SINS parameters included in the simulation. A constant value and white Gaussian noise (WGN) were added to the gyroscope and accelerometer ideal measurements.

#### 3.1. Navigation Solution Comparison.
Figure 2 shows the position errors between C-UTC and D-UTC. C-UTC refers to conventional ultratight integration, and D-UTC refers to ultratight integration with measurements difference. The red line represents the results of C-UTC, and cyan lines
Table 1: SINS simulation parameters.

| Component       | Constant | WGN |
|-----------------|----------|-----|
| Gyroscope       | 5°       | 1°  |
| WGN             |          |     |
| Accelerometer   | 10 h     | 1 h |

Figure 1: The federated filter-based GPS/SINS tight integration.

Figure 2: Continued.

(a) (b)
Figure 2: Positioning errors. (a) Latitude error. (b) Longitude error. (c) Altitude error.

Table 2: Position errors.

|            | Latitude (m) | Longitude (m) | Altitude (m) |
|------------|--------------|---------------|--------------|
|            | Mean | RMSE | Mean | RMSE | Mean | RMSE |
| D-UTC      | 1.04 | 1.21 | 1.00 | 1.34 | 0.86 | 1.16 |
| C-UTC      | 0.88 | 1.09 | 0.51 | 0.72 | 1.23 | 1.52 |

Figure 3: Continued.
Table 3: Velocity error.

|                     | East velocity (m/s) | North velocity (m/s) | Up velocity (m/s) |
|---------------------|---------------------|----------------------|-------------------|
|                     | Mean     | RMSE    | Mean     | RMSE    | Mean     | RMSE    |
| D-UTC               | 0.020    | 0.027   | 0.014    | 0.019   | 0.019    | 0.029   |
| C-UTC               | 0.019    | 0.030   | 0.024    | 0.020   | 0.017    | 0.034   |

Figure 3: Velocity error. (a) East velocity error. (b) North velocity error. (c) Up velocity error.

Figure 4: Continued.
represent the results of D-UTC. Firstly, Table 2 lists the mean values and root mean square errors (RMSE) of the position. The mean and RMSE values of latitude errors has a significant difference because of a sharp fluctuation at the beginning. Specially, longitude and altitude errors perform similar mean values and RMSE values. Secondly, Figure 3 presents the velocity errors between C-UTC and D-UTC. The red line represents the results of C-UTC, and the cyan lines represent the results of D-UTC. Table 3 lists the mean values and root mean square errors (RMSE) of the velocity. Table 3 also lists the error comparison, and it can be seen that the two methods have similar results. Thirdly, Figure 4 plots the errors of altitude errors including pitch errors, roll angle errors, and yaw angle errors. Table 4 lists the mean values and RMSE values of the three-axis angle errors. Similarly, Table 3 shows the altitude error analysis, and the two methods obtain almost identical mean values and RMSE values.

3.2. Computation Load Comparison. Table 5 gives the state and measurement vector comparison, (N) refers to the number of the available satellites. Obviously, the D-UTC has lower state and measurement vector dimension than that of C-UTC. Table 6 presents the computation load comparison of the two methods, with the computer settings (Intel Core i7 Processor, 16GB RAM), C-UTC accomplishes the integration filter within 8.56 ms (average of 100 times), and the D-UTC spends shorter time which is 5.98 ms. The efficiency obtains 30.14% improvement with the new integration filter.

4. Conclusions

This paper investigated an efficient integration method of the GPS/SINS UTC system. The method composed of two steps. The first step was the pseudorange and pseudorange rate differential method which could remove the clock bias and clock drift from the state equation, which helped to reduce the dimension of the state equation. In the second step, a federated filtering method was employed to substitute the traditional centralized Kalman filtering. The subfilters were pseudorange subfilter and pseudorange rate subfilter. The subfilters and the main filter were all Kalman filters, which aimed to reduce the dimension of the measurement matrix and improved the robustness of the system. At last, the results presented by the comparison of the position, velocity,
altitude errors, and computation load. The proposed method could reduce the computation load without heavily changing the navigation solution accuracy.

**Data Availability**

The source code used to support the findings of this study is available from the corresponding author upon request.

**Conflicts of Interest**

The authors declare no conflicts of interest regarding the publication of this paper.

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