The Model Research on Location Fusion Algorithm with Big Data Selection and Accuracy Correction

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ABSTRACT

As the requirements of smart, reliable and precise location for a vehicle, the model of fusion location algorithm with big data selection and accuracy correction is established to achieve reliable and low-cost fusion location. In this paper, the data of simple inertial navigation and the data of various positioning system sources with different errors are intelligently selected, and Kalman filtering is used to fuse the location information by the function of algorithm model, and the four kinds of location information of GPS, SINS, DR and TDOA are chosen to simulate fusion algorithm. The simulation results in MATLAB environment show that the proposed fusion location algorithm model is efficient to improve the accuracy and reliability of the location algorithm.

Keywords: Combined Location; Fusion Algorithm Model; Big Data Selection; Kalman Filtering

1. INTRODUCTION

For so many kinds of location methods, it is difficult to get reliable position with only one positioning method. So combined location is becoming more and more common in applications, which also provides a good way to make use of all kind of positioning sources with big data platform.

In terms of the moving objects positioning, reference [1] proposed a federated filtering algorithm based on adaptive Kalman filtering. Reference [2] designed a fault-tolerant federated filtering algorithm for the combined positioning system to ensure the accuracy of the system when the GPS information was interrupted. Reference [3] designed a Sage-Husa Kalman filter based on UD decomposition for the divergence phenomenon of conventional filters. Reference [4] proposed a method to integrate different sensors to correct the inertial velocity for the hybrid positioning of urban vehicles. In terms of big data fusion, reference [5] proposed the optimization of dynamic data from different data sources and proposes the big data fusion based on dynamic feature selection from different data sources. Reference [6] presented a novel technique by using a hybrid algorithm for clustering and cluster member selection in the wireless multi-sensor system.

In this paper, the fusion algorithm model is established in two steps. By obtaining location information from different system platforms and choosing reliable location parameters with intelligently-selected data, and then by choosing four source fusion data with intelligently-corrected, the fusion location algorithm is simulated to get much better location reliability and accuracy effectively.

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2. ALGORITHM MODEL OVERALL DESIGN

Kalman filtering is often used to fuse different positioning information. There are two common combinations: centralized Kalman filtering and distributed Kalman filtering. Compared with centralized filtering with poor fault tolerance, distributed filtering has the advantages of low computational complexity and high fault tolerance, and is widely used in positioning systems. Federal filter is a kind of common distributed Kalman filter and the structure as shown in the Figure 1[7].

In federal filtering, a high-reliability system is selected as the public reference system firstly, and the remaining systems are combined with the public reference system to form the subsystems which perform information optimization filtering and send the obtained information to the main filter for data fusion.

Combining different positioning methods, the optimal selection fusion localization algorithm based on big data fusion is established. Select a system with small external influence as the public reference system and define it as α. Then build subsystems and perform Kalman filtering. The filtered subsystems carry out credibility detection, which specifically includes fault detection and positioning deviation detection of the subsystems. Fault detection is used to detect the extent to which subsystems are affected by noise, and positioning deviation detection is used to detect whether the positioning values obtained by these methods are suitable for positioning judgment. Select a positioning deviation range $\Delta r^*$, if the fault-free subsystem positioning deviation satisfies:

$$KF_i - \alpha \leq \Delta r (1)$$

trust this subsystem. Untrusted subsystems are quarantined and error detection is performed on trusted subsystems. If the error of the positioning method is less than public reference system:

$$Err_{Mi} < Err_{\alpha} (2)$$

output its positioning value directly. Final positioning selection and fusion based on test results. Add other auxiliary information, such as images, to the optimized positioning results for second optimization to obtain more accurate positioning results. Figure 2 shows the optimal selection fusion location algorithm under the big data environment.
Figure 1. The structure of federal Kalman filter.

Figure 2. Optimal selection fusion location algorithm in big data environment.
3. SYSTEM MODEL ESTABLISHMENT

The public reference system is combined with remaining positioning systems to construct subsystems, and establish the corresponding state equations and measurement equations. Kalman filtering is performed on each subsystem to obtain optimal state of the subsystem.

In this design, four different positioning methods are chosen to form a combined positioning system. Selecting SINS which is not dependent on external information as the public reference system. GPS/SINS is subsystem1, DR/SINS is subsystem2, TDOA/SINS is subsystem3. The system state error is selected as the state variable to establish the state equation. Geographic coordinate system is selected as navigation coordinate system. X-axis points to the east, y-axis points to the north, and z-axis points to the sky. In carrier coordinate system, x-axis points to the right, y-axis points to the front, and z-axis points to the top.

A. GPS/SINS

SINS state error includes: attitude error $\varphi_E, \varphi_N, \varphi_U$, speed error $\delta V_E, \delta V_N, \delta V_U$, position error $\delta E, \delta \lambda, \delta H$, gyro drift $\varepsilon_E, \varepsilon_N, \varepsilon_U$, accelerometer deviation $\nabla_E, \nabla_N, \nabla_U$. GPS status error includes: speed error $\delta V_{GE}, \delta V_{GN}, \delta V_{GU}$ , position error $\delta E_G, \delta \lambda_G, \delta H_G$.

State vector:

$$X_1 = (\varphi_E, \varphi_N, \varphi_U, \delta V_E, \delta V_N, \delta V_U, \delta E, \delta \lambda, \delta H, \varepsilon_E, \varepsilon_N, \varepsilon_U, \nabla_E, \nabla_N, \nabla_U, \delta V_{GE}, \delta V_{GN}, \delta V_{GU}, \delta E_G, \delta \lambda_G, \delta H_G)^T$$

(3)

State equation:

$$\dot{X}_1 = F_1X_1 + W_1$$

(4)

State transformation matrix:

$$F_1 = \begin{bmatrix} F_{SINS} & 0 \\ 0 & F_{GPS} \end{bmatrix}$$

(5)

$F_{SINS}$ is SINS state transformation matrix. $F_{GPS}$ is GPS state transformation matrix.

SINS and GPS speed measurement differences and position measurement differences are selected as the measurement equation:

$$Z_1 = \begin{bmatrix} V_{SINS} - V_{GPS} \\ P_{SINS} - P_{GPS} \end{bmatrix} = H_1X_1 + V_1$$

(6)

Measurement matrix:

$$H_1 = \begin{bmatrix} 0_{3\times3} & I_{3\times3} & 0_{3\times3} & 0_{3\times6} & -I_{3\times3} & 0_{3\times3} \\ 0_{3\times3} & 0_{3\times3} & I_{3\times3} & 0_{3\times6} & 0_{3\times3} & -I_{3\times3} \end{bmatrix}$$

(7)
B. DR/SINS

The SINS state variables are selected the same as subsystem1, DR state variables select position error $\delta E_D, \delta \lambda_D, \delta H_D$ and odometer scale factor error $\delta K_D$ [8].

State vector:

\[
X_2 = 
(\varphi_E, \varphi_N, \varphi_U, \delta V_E, \delta V_N, \delta V_U, \delta E, \delta \lambda, \delta H, \varepsilon_E, \varepsilon_N, \varepsilon_U, \nabla_E, \nabla_N, \nabla_U, \delta E_D, \delta \lambda_D, \delta H_D, \delta K_D)^T
\] (8)

State equation:

\[
\dot{X}_2 = F_2 X_2 + W_2 (9)
\]

$F_2$ is the combination of state transition matrix for SINS and DR.

Select SINS and DR position measurement differences as the measurement equation:

\[
Z_2 = [P_{SINS} - P_{DR}] = H_2 X_2 + V_2 (10)
\]

Measurement matrix:

\[
H_2 = \begin{bmatrix}
0_{3\times6} & I_{3\times3} & 0_{3\times6} - I_{3\times3} & 0_{3\times1}
\end{bmatrix}
\] (11)

C. TDOA/SINS

The state error of SINS is selected as the state vector $X_3$ [9].

State equation:

\[
\dot{X}_3 = F_3 X_3 + W_3 (12)
\]

State transformation matrix:

\[
F_3 = F_{SINS} (13)
\]

The measurement equation selects SINS and TDOA position measurement differences:

\[
Z_3 = [P_{SINS} - P_{TDOA}] = H_3 X_3 + V_3 (14)
\]

Measurement matrix:

\[
H_3 = \begin{bmatrix}
0_{3\times6} & I_{3\times3} & 0_{3\times6}
\end{bmatrix}
\] (15)
4. SYSTEM DETECTION AND RECONSTRUCTION

System detection includes the credibility detection which involves fault detection and positioning deviation detection of each subsystem, and the error detection of positioning methods.

An important feature of the combined positioning system is fault tolerance, which is reflected in fault detection and reconstruction[10]. The system has self-monitoring capability, it can monitor operating status in real time and detect faults to reconfigure the system. Fault detection using Chi-square test. Based on the status of subsystems, the fault detection function is established[11][12]. Judging whether the subsystem is faulty according to the fault detection result, and positioning deviation detection using (1) as a criterion.

Appropriate reference errors is used to determine which subsystems are selected for information fusion. The model of optimal selection fusion location algorithm proposed in this paper, positioning error of the public reference system is selected as reference error. The fused information is still selected in the case where the positioning method error is smaller than public reference system positioning error, the final positioning effect cannot be optimal. System reconstruction based on the test results.

![Flowchart of System Detection and Reconstruction](image)

Figure 3. Simulation system detection and reconstruction.

This paper only simulates the first-level optimization of the algorithm. Simulation system detection and reconstruction shown in Figure 3. The GPS with the highest positioning accuracy compared to other positioning methods is easily affected by external noise. In order
to make full use of positioning information to obtain relatively accurate positioning results, credibility detection of subsystems and error detection of trusted subsystems are required before information fusion. The credibility test is used to detect three subsystems, and the error detection mainly detects the GPS positioning error under the premise of subsystem 1 being reliable.

Subsystem 1 is isolated when it is not trusted and SINS positioning information is output when all subsystems are not trusted.

If GPS positioning can be used for system positioning judgment, it is divided into two cases: One is that GPS positioning error is very small and can be considered as an ideal state, positioning information fusion will reduce the system accuracy. Therefore, the GPS positioning information is directly used as the final positioning result. Second, subsystem 1 is reliable but the GPS positioning error is large. In this case, the specific location information screening and fusion is performed on the premise of reliably detecting the other two subsystems. Since the subsystem filtering is a correction to the SINS positioning information, the determination of whether the GPS positioning information can be used directly is based on the SINS positioning error. If GPS positioning error is smaller than SINS positioning error, that is, if the (2) is satisfied, it is the first case, otherwise it is the second case. Similarly, the above method is used to judge the use of data in the other two subsystems.

5. ALGORITHM SIMULATION

The simulation was performed in MATLAB R2017a environment and the first-order optimization of the algorithm was simulated. The initial conditions for the simulation are set to: Gyro constant drift $0.01^\circ/h$, gyro angle walk coefficient $0.001^\circ/\sqrt{h}$, accelerometer drift $100\mu g$, accelerometer walking coefficient $10\mu g/\sqrt{Hz}$, attitude error $[30' 30' 30']^T$, initial velocity error $0.1m/s$, initial position error $10m$, odometer calibration coefficient error $0.01$, simulation time is $1100s$, sampling period is $0.1s$, false alarm rate of fault detection is $0.005$, subsystem1 threshold value $41.401$, subsystem2 threshold value $38.582$, subsystem3 threshold value $32.801$. Simulation algorithm block diagram shown in Figure 4.
Figure 4. Simulation algorithm block diagram.

Figure 5. Positioning trajectory and error under GPS ideal conditions.
Figure 6. Positioning trajectory and error under GPS weak interference.

Figure 7. Positioning trajectory and error under GPS strong interference.
Figure 5 shows the positioning trajectory and positioning error in two different ways of simple fusion positioning and selective fusion positioning under the premise of ideal GPS positioning. In the trajectory map, it can be seen that selects the GPS positioning trajectory as the final positioning result substantially coincides with the real trajectory. From the error chart, we can see that the positioning error obtained by the optimal selection fusion location algorithm is within ±20m, simple fusion positioning error reaches ±150m.

Figure 6 shows the positioning trajectories and errors when both GPS and TDOA are disturbed. Error chart shows that the optimal selection fusion location algorithm locates errors within ±100m, simple fusion positioning error reaches ±250m. When subsystem 1 is reliable but GPS positioning is disturbed, if TDOA is also interfered, the positioning error will increase unnecessarily when using simple information fusion. Instead, selective fusion of positioning data can significantly improve the positioning results.

When GPS is subjected to strong interference during positioning, it can be seen from the GPS-SINS positioning trajectory in figure 7 that GPS positioning is not suitable for final positioning. If the information fusion of the main filter is performed directly, although the final positioning result is better than the positioning result of the subsystem 1, there is still a certain degree of error. The positioning error obtained by the optimal selection fusion location algorithm is within ±50m, simple fusion positioning error reaches ±150m. With the optimal selection fusion location algorithm, it can be seen that both the positioning trajectory and the positioning error are improved.

6. CONCLUSIONS

To obtain the best location information in the big data environment, choosing the appropriate location source information for integration is important. The reliability of different positioning sources are different, and sometimes, the final result will be unsatisfactory if the information fusion is performed blindly. An intelligent optimal selection fusion location algorithm which selects and fuses multiple positioning source information based on big data environment is proposed in this paper, the results obtained have improved positioning accuracy and reliability. First-level optimization simulation proves that positioning accuracy has been improved apparently.

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