A Novel Vehicular Integrated Positioning Algorithm

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Abstract. The Global navigation satellite system (GNSS) can offer high precise location service for vehicle in open area, but in urban, the satellite signal is obscured by dense building, tunnel. Dead reckoning (DR) system can estimate vehicular position in short period of time, but do not work well as its error accumulation with the passage of time. If the area has been deployed RSU, vehicle can get own position by communication. A single positioning system is not able to offer precise location service in urban, this paper combines with RSU, GNSS and DR and proposes a integrated position system. The integrated system makes use of Federate Kalman Filter (FKF) algorithm to realize information fusion of three systems. The experimental results show the positioning accuracy and anti-jamming capability of RSU/GNSS/DR integrated positioning system is better than a single system.

Keywords: Vehicle positioning · Information fusion · Federate Kalman Filter · Integrated positioning system

1 Introduction

GNSS has some advantages such as high precision, low cost, ease of use, as long as it can receive the satellite signal where the vehicular absolute position can be calculated, and the positioning error will not accumulate with the passage of time. However, in the city, as the satellite signals are obscured by dense buildings, the positioning accuracy decline, when the satellite positioning system is used alone. Even more serious is that the vehicle can not positioning in the tunnel, so the positioning system has lower reliability [1, 2]. Dead reckoning (DR) system is commonly used in the autonomous positioning method for a vehicle. As long as vehicular initial position is set, DR system can calculate the vehicular current position by speed and direction, and can provide high-precision positioning in a short time. If the initial position of the DR system can not be calibrated during a shorter period of time, because of its error accumulation with the passage of time, positioning system's reliability is also declined [3, 4]. With the development of VANET, RSU-based positioning system has been applied [5, 6]. Using three times communication between vehicle and RSU, RSU-based positioning system do not rely on satellites to provide location service for the vehicle, if the positioning

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areas have employed RSU. Positioning accuracy is in direct proportion to RSU-employed intensity [7], the more RSU deployment, the higher positioning precision, but the higher the cost. These three systems have advantages and disadvantages, but in a complex environment, a single system can not satisfy the application requirements of current vehicle positioning, using information fusion technology to improve the reliability and accuracy of the positioning system, it will be a viable solution for vehicle location [8].

This paper will combine with RSU, GNSS and DR systems and proposed a integrated positioning system for vehicular location service. In Sect. 2, we introduce the designation of integrated positioning system. Section 3 makes positioning experiment to verify the validity of the proposed algorithm. Section 4 this paper gives a conclusion and discusses some open issues.

2 RSU/GNSS/DR Integrated Positioning Algorithm Designation

In order to solve the vehicle positioning problem in complex urban environment, vehicular positioning solution needs to integrate multiple positioning technologies to realize high-precision, high-reliability positioning. As centralized Kalman Filter integrated algorithm has some problems such as heavy calculation burden, faulted subsystem isolation is difficult, it can not be up to multi-dimensional information fusion vehicular positioning. This section will discuss the RSU/GNSS/DR integrated positioning assisted by FKF algorithm to offer vehicular location service.

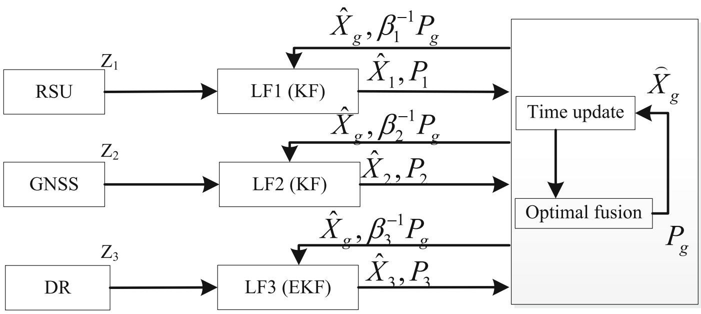

Fig. 1. The framework of RSU/GNSS/DR integrated positioning system

RSU-based positioning subsystem uses a linear Kalman Filter as the Local Filter, names as LF1, the corresponding information sharing coefficient is β_1; GNSS positioning subsystem also uses a linear Kalman filter, names as LF2, the corresponding information sharing coefficient is β_2; DR positioning subsystem uses extended Kalman Filter (EKF), names as LF3, the corresponding information sharing coefficient is β_3; main filter is responsible to information fusion, the framework of RSU/GNSS/DR integrated positioning system is shown in Fig. 1.

2.1 System State Equation and Observation Equation

Using "current" statistic model to describe the statistical distribution of the vehicle acceleration, the significance of this model is that, people merely concern about the "current" probability density of maneuvering acceleration, i.e. current probability of vehicle maneuvering, when a vehicle maneuver in a positive acceleration, which in the next instantaneous acceleration value range is limited, and only in the adjacent range of the current acceleration, which is shown in Eq. (1).

$$\begin{aligned} a_1(t) &= \bar{a}(t) + a(t) \\ \dot{a}(t) &= -\frac{1}{\tau}a(t) + w(t) \\ \dot{a}(t) &= -\frac{1}{\tau}a_1(t) + \frac{1}{\tau}\bar{a}(t) + w(t) \end{aligned} \tag{1}$$

where, $a_1(t)$ is maneuvering acceleration, its variance is σ^2, $\bar{a}(t)$ is the "current" mean of maneuvering acceleration, $\bar{a}$ is constant in each sampling cycle. $a(t)$ is colored acceleration noise with zero mean, $w(t)$ is White Gaussian Noise with zero mean, τ is correlative time constant of maneuvering acceleration change rate.

The state equation of integrated positioning algorithm is $X = [x_e, v_e, a_e, x_n, v_n, a_n]^T$, where x_e and x_n are the easterly and northerly location component respectively (units: m), v_e and v_n are the easterly and northerly velocity component respectively (units: m/s), a_e and a_n are the easterly and northerly acceleration component respectively (units: m/s^2). The state equation of integrated system can be represented by Eq. (2).

$$\hat{X}(t) = AX(t) + U + W(t) \tag{2}$$

where,

$$A = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & -1/\tau_{a_e} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & -1/\tau_{a_n} \end{bmatrix}, \ U = \begin{bmatrix} 0 \\ 0 \\ \frac{1}{\tau_{a_e}}\bar{a}_e \\ 0 \\ 0 \\ \frac{1}{\tau_{a_n}}\bar{a}_n \end{bmatrix}, \ W(t) = \begin{bmatrix} 0 \\ 0 \\ w_{a_e} \\ 0 \\ 0 \\ w_{a_n} \end{bmatrix}$$

w_{a_e} and w_{a_n} are White Gaussian Noise, whose means are zero, variances are $\sigma^2_{a_e}$ and $\sigma^2_{a_n}$ respectively, τ_{a_e} and τ_{a_n} are easterly and northerly correlative time constant of maneuvering acceleration change rate respectively, $\bar{a}_e$ and $\bar{a}_n$ are easterly and northerly "current" mean of maneuvering acceleration component respectively.

Presupposed the sampling cycle is T, by discretizing continuous system state equation, the discrete system state equation can be derived.

$$X(k) = \Phi(k/k-1)X(k/k-1) + U(k) + W(k) \tag{3}$$

where, $X(k) = [x_e(k), v_e(k), a_e(k), x_n(k), v_n(k), a_n(k)]^T$

$$\Phi(k/k-1) = diag[\Phi_e(k/k-1), \Phi_n(k/k-1)] \tag{4}$$

set $\alpha_e = \frac{1}{\tau_{a_e}}$, $\alpha_n = \frac{1}{\tau_{a_n}}$, $\Phi_e(k/k-1)$ and $\Phi_n(k/k-1)$ are

$$\Phi_e(k/k-1) = \begin{bmatrix} 1 & T & \alpha_e^{-2}(-1+\alpha_e T + e^{-\alpha_e T}) \\ 0 & 1 & (1-e^{-\alpha_e T})\alpha_e^{-1} \\ 0 & 0 & e^{-\alpha_e T} \end{bmatrix},$$
$$\Phi_n(k/k-1) = \begin{bmatrix} 1 & T & \alpha_n^{-2}(-1+\alpha_n T + e^{-\alpha_n T}) \\ 0 & 1 & (1-e^{-\alpha_n T})\alpha_n^{-1} \\ 0 & 0 & e^{-\alpha_n T} \end{bmatrix}$$

$$U(k) = [u_1 \quad u_2 \quad u_3 \quad u_4 \quad u_5 \quad u_6]^T \tag{5}$$

where,

$$\begin{aligned} u_1 &= \left[-T + 0.5\alpha_e T^2 + (1-e^{-\alpha_e T})\alpha_e^{-1}\right]\alpha_e^{-1}\bar{a}_e \\ u_2 &= \left[T - (1-e^{-\alpha_e T})\alpha_e^{-1}\right]\bar{a}_e \\ u_3 &= (1-e^{-\alpha_e T})\bar{a}_e \\ u_4 &= \left[-T + 0.5\alpha_n T^2 + (1-e^{-\alpha_n T})\alpha_n^{-1}\right]\alpha_n^{-1}\bar{a}_n \\ u_5 &= \left[T - (1-e^{-\alpha_n T})\alpha_n^{-1}\right]\bar{a}_n \\ u_6 &= (1-e^{-\alpha_n T})\bar{a}_n \end{aligned}$$

2.1.1 RSU Observation Equation

According to positioning theory of the RSU-based subsystem, we set the system state variable $X_1 = X$, subsystem state equation is same as system state equation.

The observation values, who is output of RSU-based positioning subsystem, are easterly and northerly coordinates component e_{obs} and n_{obs} (units: m), the observation equation is represented by Eq. (6)

$$Z_1(k) = H_1(k)X_1(k) + V_1(k) \tag{6}$$

where,

$$Z_1(k) = \begin{bmatrix} e_{obs}(k) \\ n_{obs}(k) \end{bmatrix}, \quad V_1(k) = \begin{bmatrix} w_e(k) \\ w_n(k) \end{bmatrix}, \quad H_1(k) = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \end{bmatrix},$$

$w_e(k)$ and $w_n(k)$ are White Gaussian Noise, whose means are zero, variance are σ_e^2 and σ_n^2 respectively, $w_e(k)$ and $w_n(k)$ refer to easterly and northerly position measurement noise measured by the RSU positioning device, measurement noise covariance matrix is represented by $R(k)$, where, $R(k) = diag(\sigma_{a_e}^2, \sigma_{a_n}^2)$.

2.1.2 GNSS Observation Equation

GNSS subsystem is similar to RSU-based subsystem, we set the system state variable $X_2 = X$, subsystem state equation is same as system state equation. The observation values are easterly and northerly coordinates component e_{obs} and n_{obs}, the observation equation can be represented by Eq. (7).

$$Z_2(k) = H_2(k)X_2(k) + V_2(k) \tag{7}$$

where,

$$Z_2(k) = \begin{bmatrix} e_{obs}(k) \\ n_{obs}(k) \end{bmatrix}, \quad V_2(k) = \begin{bmatrix} w_e(k) \\ w_n(k) \end{bmatrix}, \quad H_2(k) = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$w_e(k)$ and $w_n(k)$ are easterly and northerly measurement error, whose means are zero, variance are σ_e^2 and σ_n^2 respectively. Measurement noise covariance matrix is $R(k) = diag(\sigma_{a_e}^2, \sigma_{a_n}^2)$.

2.1.3 DR Observation Equation

The state variable of DR subsystem is $X_3 = X$, the observation values, who are the output of angular rate gyroscope ω and the output of the vehicle odometer S in a sampling cycle, the subsystem observation equation can be represented by Eq. (8).

$$Z_3(t) = h_3(t, X_3(t)) + V_3(t) \tag{8}$$

where,

$$Z_3 = \begin{bmatrix} \omega \\ s \end{bmatrix} = \begin{bmatrix} \frac{\partial}{\partial t}\left[\tan^{-1}\left(\frac{v_e}{v_n}\right)\right] \\ \varphi T\sqrt{v_e^2 + v_n^2} \end{bmatrix} + \begin{bmatrix} \varepsilon_\omega \\ \varepsilon_s \end{bmatrix}$$

after reduction,

$$Z_3 = \begin{bmatrix} \omega \\ s \end{bmatrix} = \begin{bmatrix} \frac{v_n a_e - v_e a_n}{v_e^2 + v_n^2} \\ T\sqrt{v_e^2 + v_n^2} \end{bmatrix} + \begin{bmatrix} \varepsilon_\omega \\ \varepsilon_s \end{bmatrix}$$

A calibration factor φ is assumed as 1, ε_ω is the gyroscope drift, approximate to $(0, \sigma_\omega^2)$ White Gaussian Noise, ε_s is the observation noise of odometer output S, approximate to $(0, \sigma_s^2)$ White Gaussian Noise, $R(k)$ is measurement noise covariance matrix, $R(k) = diag(\sigma_{a_\omega}^2, \sigma_{a_s}^2)$. After discretizing continuous observation equation, the discrete observation equation is shown in Eq. (9)

$$Z_3(k) = h_3[k, X_3(k)] + V_3(k) \tag{9}$$

DR employs EKF as local filter, and lets $h_3[X_3(k)]$ to expand in the vicinity of $\hat{X}(k/k-1)$ according to Taylor series. Ignoring secondary or higher order entry, DR can obtain linear observation equation.

$$Z_3(k) = H_3(k)X_3(k) + h_3\left[k, \hat{X}_3(k/k-1)\right] - H_3(k)\hat{X}_3(k/k-1) + V_3(k) \tag{10}$$

where,

$$H_3(k) = \left.\frac{\partial h_3[X_3(k)]}{\partial X_3(k)}\right|_{X_k=\hat{X}_{k,k-1}} = \begin{bmatrix} 0 & h_1 & h & 0 & h_3 & h_4 \\ 0 & h_5 & 0 & 0 & h_6 & 0 \end{bmatrix}$$

$$h_1 = \frac{\hat{a}_n(k/k-1)\hat{v}_e^2(k/k-1) - 2\hat{v}_e(k/k-1)\hat{v}_n(k/k-1)\hat{a}_e(k/k-1) - \hat{a}_n(k/k-1)v_n^2(k/k-1)}{\left[v_e^2(k/k-1) + v_n^2(k/k-1)\right]^2}$$

$$h_2 = \frac{\hat{v}_n(k/k-1)}{v_e^2(k/k-1) + v_n^2(k/k-1)}$$

$$h_3 = \frac{\hat{a}_e(k/k-1)\hat{v}_e^2(k/k-1) - 2\hat{v}_e(k/k-1)\hat{v}_n(k/k-1)\hat{a}_e(k/k-1) - \hat{a}_n(k/k-1)v_n^2(k/k-1)}{\left[v_e^2(k/k-1) + v_n^2(k/k-1)\right]^2}$$

$$h_4 = \frac{\hat{v}_e(k/k-1)}{v_e^2(k/k-1) + v_n^2(k/k-1)}$$

$$h_5 = \frac{T\hat{v}_e(k/k-1)}{\sqrt{v_e^2(k/k-1) + v_n^2(k/k-1)}}$$

$$h_6 = \frac{T\hat{v}_n(k/k-1)}{\sqrt{v_e^2(k/k-1) + v_n^2(k/k-1)}}$$

2.2 Time Update and Measurement Update of Subsystem

LF1 and LF2 subsystem time update and measurement update equation:

$$\hat{X}_i(k/k-1) = \Phi(k/k-1)\hat{X}_i(k-1) + U(k-1) \tag{11}$$

$$P_i(k/k+1) = \Phi(k/k-1)P_i(k-1)\Phi^T(k/k-1) + Q(k-1) \tag{12}$$

$$K_i(k) = P_i(k/k-1)H_i^T(k)\left[H_i(k)P_i(k/k-1)H_i^T(k) + R_i(k)\right]^{-1} \tag{13}$$

$$\hat{X}_i(k) = \hat{X}_i(k/k-1) + K_i(k)[Z_i(k) - H_i(k)X_i(k/k-1)] \tag{14}$$

$$P_i(k) = [1 - K_i(k)H_i(k)]P_i(k/k-1) \tag{15}$$

State transition matrix: the prediction value of acceleration is considered as the mean of "current" acceleration, i.e.

$$\bar{a}_e(k) = \hat{a}_e(k/k-1),\ \bar{a}_n(k) = \hat{a}_n(k/k-1)$$

Equation (11) can be simplified to Eq. (16)

$$\hat{X}_1(k/k-1) = \Phi(k/k-1)\hat{X}_1(k-1) \tag{16}$$

where, $\Phi(k/k-1) = diag[\Phi_e(T), \Phi_n(T)]$, i.e.

$$\Phi_e(T) = \begin{bmatrix} 1 & T & T^2/2 \\ 0 & 1 & T \\ 0 & 0 & 1 \end{bmatrix}, \quad \Phi_n(T) = \begin{bmatrix} 1 & T & T^2/2 \\ 0 & 1 & T \\ 0 & 0 & 1 \end{bmatrix}$$

System noise covariance matrix: $Q(k-1)$ is the discrete matrix of system noise covariance matrix Q

$$Q(k-1) = \begin{bmatrix} \frac{2\sigma_{a_e}^2}{\tau_{a_e}} Q_e(T) & 0_{3\times3} \\ 0_{3\times3} & \frac{2\sigma_{a_n}^2}{\tau_{a_n}} Q_n(T) \end{bmatrix}$$

where,

$$Q_e(T) = Q_n(T) \approx \begin{bmatrix} T^5/20 & T^4/8 & T^3/6 \\ T^4/8 & T^3/3 & T^2/2 \\ T^3/6 & T^2/2 & T \end{bmatrix}.$$

DR subsystem employs EKF as the local filter LF3, the computing process is different from the LF1 and LF2, which is shown in Eq. (17).

$$\begin{aligned}
&\hat{X}_3(k/k-1) = \Phi(k/k-1)\hat{X}_3(k-1) \\
&P_3(k/k+1) = \Phi(k/k-1)P_3(k-1)\Phi^T(k/k-1) + Q(k-1) \\
&K_3(k) = P_3(k/k-1)H_3^T(k)\left[H_3(k)P_3(k/k-1)H_3^T(k) + R_3(k)\right]^{-1} \\
&\hat{X}_3(k) = \hat{X}_3(k/k-1) + K_3(k)[Z_3(k) - h_3(k, X_3(k/k-1))] \\
&P_3(k) = [1 - K_3(k)H_3(k)]P_3(k/k-1)
\end{aligned} \tag{17}$$

where, $Q(k-1)$ and $\Phi(k/k-1)$ is same as one of LF1 and LF2.

2.3 Global Information Integration and Information Sharing

Global information integration:

$$\begin{aligned}
&\hat{X}_g(k) = P_g(k)\left[P_1^{-1}(k)\hat{X}_1(k) + P_2^{-1}(k)\hat{X}_2(k) + P_3^{-1}(k)\hat{X}_3(k)\right] \\
&P_g^{-1}(k) = P_1^{-1}(k) + P_2^{-1}(k) + P_3^{-1}(k) \\
&Q_g^{-1}(k) = Q_1^{-1}(k) + Q_2^{-1}(k) + Q_3^{-1}(k)
\end{aligned} \tag{18}$$

Information sharing:

$$\begin{cases} Q_i(k) = \beta_i^{-1} Q_g(k) \\ P_i(k) = \beta_i^{-1} P_g(k) \quad i = 1, 2, 3 \\ \hat{X}_i(k) = \hat{X}_g(k) \end{cases} \tag{19}$$

where, $\beta_1 + \beta_2 + \beta_3 = 1$.

3 Testing and Analysis

3.1 The Vehicular Testing Scenario

The testing scenario is shown in Fig. 2, the route from the start point to the end point along the arrow direction, khaki route is the predetermined moving route, the whole testing route can be divided into three zones. First, open area, in where the satellite signal is not blocked; second, tunnels, in where almost all of the satellite signal is blocked; and third, the are is beside buildings, in where part of the satellite signal is blocked. This testing scenario simulates different situation of the vehicle on the road, the reliability and positioning accuracy of integrated positioning system can be test.

We mainly simulate the RSU-failed situation in first area, so we do not deploy RSU in first area, the vehicle depends on multimode GNSS subsystem to offer location service. In second area, we test the positioning performance of integrated system in GNSS-failed situation, so we deploy 7 RSUs (red point in Fig. 2), and preset the UTM

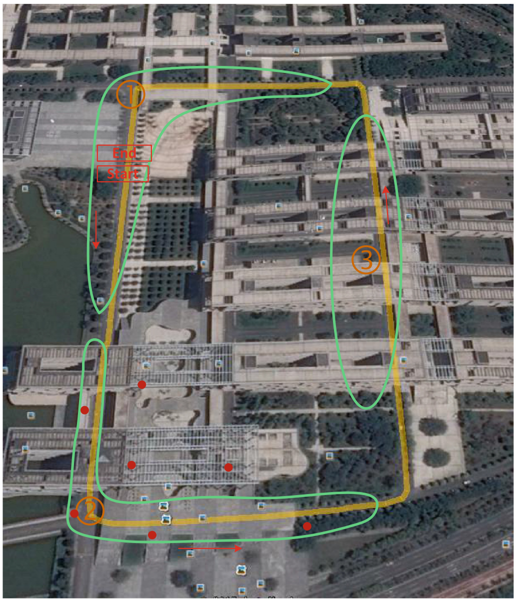

Fig. 2. The testing scenario (Color figure online)

coordinates. In third area, we test the positioning performance of GNSS/DR in RSU-failed situation, which will be influenced by building.

3.2 Vehicular Positioning and Result Analysis

3.2.1 Testing Process

According to predetermined route in testing scenario, the whole test is divided into GNSS-only positioning experiment, RSU-only positioning experiment, RSU/GNSS/DR integrated positioning system experiment. The test process is as follows:

1. **Device Initialization.** Set the UART parameter (the port number: COM6 and baud rate: 4800Bd) for multimode GNSS receiver, set the GNSS data storage directory, set the DSRC receiver channel (CH182) and data storage directory of vehicular RSU-based positioning subsystem, set the initial position of the DR subsystem.
2. **Time Calibration.** In order to maintain time synchronization in GNSS and DSRC, calibration of both time reference.
3. **Location data acquisition.** Vehicle tracks the khaki line at a steady speed of 20 km/h, get location data by integrated positioning system.
4. **Coordinate transformation.** GPS output format is latitude and longitude coordinates, location data format of RSU-based subsystem is UTM coordinate. Since the coordinate system is different in subsystems, we need to achieve coordinate transformation in order to calculate the vehicular coordinates.
5. **Information fusion.** Using output of three positioning subsystems, the integrate system calculates vehicular coordinates by information fusion algorithm.
6. **Trajectory display.** Using the output data of integrated system to generate KML files, and then displays the testing trajectory on Google Earth software.

3.2.2 Positioning Result and Analysis

From the Fig. 3, we can know that, in fist area, the moving trajectory of the integrated system is much same as GNSS' one. The multimode GNSS receiver can receive both BeiDou System (BDS) and Global Positioning system (GPS) satellite signal, and can capture 8–9 satellites simultaneously during the test process. The RSU-based subsystem is considered as a fault system and isolated by integrated system. The positioning output of GNSS/DR play a leading role, the 2DRMS of positioning accuracy is not larger than 2 m.

In second area, the situation is just the opposite. The multimode GNSS receiver can not receive the signal in tunnel. From the green trajectory, we can see that the positioning accuracy decline rapidly. The GNSS is regarded as a fault subsystem, and is isolated by integrated system. The positioning output of RSU/DR play a leading role, and the accuracy is better than the accuracy of RSU-only positioning system, the 2DRMS of positioning accuracy is not larger than 2 m.

In third area, as the RSU communication range do not cover this area, so RSU subsystem is isolated by integrated system, the GNSS/DR offer the positioning service. But the performance of GNSS/DR is influenced by building, the positioning output deviate the road. At the front half of the trip in the third area, the positioning error is corrected by DR subsystem. But at the latter half of the trip, the error is accumulated gradually as time goes on, the DR subsystem is regarded as fault system by fault detected algorithm, GNSS subsystem does well only in this situation. If we deploy RSUs for vehicular positioning in this special area, the accuracy will be improved (Fig. 4).

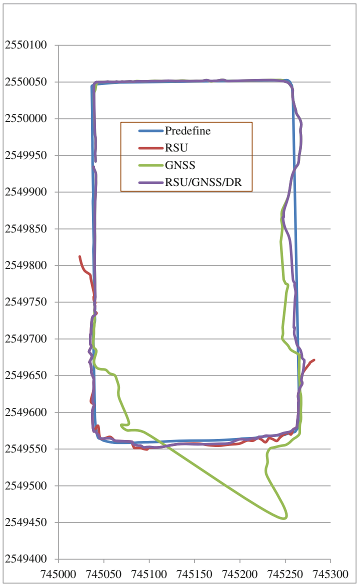

Fig. 3. The comparison chart of positioning accuracy (Color figure online)

Fig. 4. The result of RSU/GNSS/DR integrated positioning

From the positioning testing and analysis abovementioned, the integrated positioning system is up to vehicular positioning in urban, and the positioning accuracy can meet road-level requirement.

4 Conclusion and Discussion

Federal Kalman Filter has been identified as the common mode filter of next-generation navigation system by Air Force, due to its flexible design, a small amount of calculation, good fault tolerance. FKF, who is composed of several sub filters and a main filter, is a two-step cascade of decentralized filtering method, which uses information sharing to achieve global optimization. For vehicle navigation and positioning, FKF has the following advantages over centralized filtering method.

Firstly, the filtered fault tolerance is better. Once a subsystem malfunction, FKF can easily detect and isolate faulted subsystem, and can employ the remaining subsystem to reconstruct the new filter, and calculate the required filter solution.

Secondly, the synthesis filtering algorithm is simper, has lighter computation burden, and less data communication, which is conductive to real-time execution in onboard devices. As a result of using the decentralized two-stage filter program, so the dimension of the filter has been greatly decreased, and reduce the amount of calculation. Vehicular embedded device computing power is weaker than personal computer, the Federal filter can run on the resource-constrained hardware platform.

Thirdly, good scalability. We can be easy to extend this algorithm by adding a map matching algorithm or vision-based positioning algorithm in future study.

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