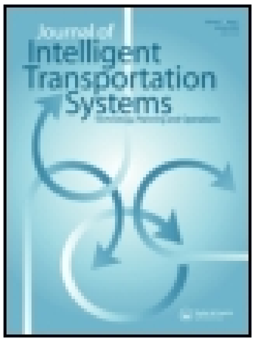

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Development and Application of an Enhanced Kalman Filter and Global Positioning System Error-Correction Approach for Improved Map-Matching

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Map-matching, which reconciles a vehicle's location with the underlying road map, is a fundamental function of a land vehicle navigation system. This article presents an improved Kalman filter approach whose state-space model is different from the conventional ones. The main objective of the research is to develop and apply a proper Kalman filter–based model for effectively correcting Global Positioning System (GPS) errors in map-matching. Based on the in-depth investigation of the characteristics of GPS errors, the authors presents a novel approach to update the state vector and other related parameters of the Kalman filter using both the historical tracks and road map information. The performance of the proposed approach is thoroughly examined by sample applications with real field data. The result shows that it handles the biased error and the random error of the GPS signals reasonably well in both the along-road and cross-road directions.

Keywords Global Positioning System; Kalman filter; map-matching; vehicle navigation system

BACKGROUND AND LITERATURE REVIEW

The Global Positioning System (GPS)-based vehicle navigation systems have been the focus of researchers and practitioners for many years. Although the accuracy of an independent GPS navigation system may be less promising than that of an integrated system with multiple sensors, it remains the mainstream civilian vehicle navigation application due, in part, to its low-cost and easy installation.

The process that a vehicle navigation system uses to translate the measured position onto the road map is known as map-matching (French, 1986; Quddus, Ochieng, and Liu, 2008). Under the assumption that the underlying road networks are accurate, the map-matching task is to obtain the most accurate vehicle location by using GPS tracks and the underlying road maps. The performance of a vehicle navigation device depends largely on the accuracy of the map-matching algorithm.

Among the traditional map-matching algorithms, the most common method is the geometric analysis approach that uses the geometric information of the road network (Duan, Bao, and Yang, 1998; Joshi, 2001; Kim, Lee, Kang, Lee, and Kim, 1996). White, Bernstein, and Kornhauser (2000) conducted a comparison analysis of existing geometric map-matching algorithms including point-to-point, point-to-curve, and curve-to-curve approaches, and they concluded that the accuracy problem could not be solely resolved by the geometric map-matching approach. Another typical method is the topological approach that uses the link's geometry, connectivity, and contiguity in the map-matching process (Chen, Li, Meng, and Chen, 2003; Greenfeld, 2002; Meng, Chen, Chen, and Chao, 2003). Quddus, Ochieng, Zhao, and Noland (2007) pointed out that most of the topological approaches are sensitive to outliers and unreliable at junctions where the bearings of the connecting roads are not similar. Honey et al. (1989) proposed a probabilistic map-matching algorithm that requires the definition of an elliptical or

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rectangular confidence region around a position fix obtained from a navigation sensor. Ochieng, Quddus, and Noland (2004) further developed an enhanced probabilistic algorithm that could identify the switching of the vehicle from one link to another. Smaili, Najjar, and Charpillet (2008) used hybrid Bayesian network to further improve the accuracy.

Researchers also use the Kalman filter (e.g., Jo, Haseyamai, and Kitajima, 1996; Kim, Jee, and Lee, 2000), belief theory (e.g., Najjar and Bonnifait, 2003; Yang, Cai, and Yuan, 2003), and the fuzzy logic model (Kim and Kim, 1999; Syed and Cannon, 2004) in the map-matching process. With these efforts, the accuracy of these algorithms for road identification has been improved significantly, and the attention now is focused on improving the accuracy of the mapped locations on the identified road. One of the most often used methods is vertical mapping, which maps the GPS tracks onto the corresponding road links vertically. The major limitation of vertical mapping is that it considers only the GPS error perpendicular to the road and does not correct its component in the road direction. Another popular method is to involve the map data and the vehicle's speed and heading information from GPS receivers in the calculation process. There are, however, problems with this approach as well. One major problem is that there is no effective way to get the accurate initial position of the subject vehicle in real time, which is a prerequisite of this approach. In addition, the speed and heading information from GPS receivers contain errors too. Indeed, the speed and heading errors from GPS receivers are often more serious than the GPS location errors.

Some new methods were proposed recently. For example, Quddus, Noland, and Ochieng (2006) developed an improved approach to enhance the process of locating vehicles on the selected road link. It combines the two methods previously described and gives an estimated location according to the covariance of different errors. Although the algorithm was designed for the navigation systems with two or more sensors (a GPS receiver with a deduced reckoning sensor), it could be used in the systems equipped with GPS only with the error variance–covariance matrix from navigation systems. One problem with this algorithm is that it is restricted by the accuracy of initial positions of the subject vehicle in real time. Our study of literature shows that accurately mapping the vehicle's location onto the identified road link remains a challenging task in map-matching, especially when GPS is the sole resource for navigation.

The Kalman filter is one of the most effective methods to filter signals with random noise (Brown and Hwang, 1992; Kalman, 1960; Welch and Bishop, 1995). Many researchers have applied the Kalman filter theory to their map-matching models. A notable study in the literature is the work of Kim et al. (2000), in which a map-matching algorithm was proposed consisting of a model of biased error and a Kalman filter. Their research estimates a large bias as the main source of errors and uses the estimation to correct the bias error of GPS. They suggested that the GPS error is not a white Gaussian but instead biased because of factors such as the atmospheric delay, implying that the GPS error comprises both the biased error and the white noise error. The algorithm reduced the GPS error by using the estimated value of the biased error obtained by the Kalman filter and the tracks on the crossroads or curved roads. Unfortunately, the algorithm does not handle random GPS error and its correction to the biased GPS error is sensitive to the angle of the crossroad. If the angle of the crossroad is small, the estimation of the biased error deviates largely from the actual value. As a result, the algorithm fails to correct the biased GPS error in the road direction effectively.

The key point of using a Kalman filter in map-matching is to design a new state-space model that satisfies the fundamental assumptions of the Kalman filter theory. This article presents an improved Kalman filter algorithm and an effective GPS error correction approach. The method consists of a Kalman filter and a novel method to minimize the biased error of GPS after the vehicles make turns. The Kalman filter state-space model makes use of the characteristics of GPS errors and takes into consideration the white noise assumption of the Kalman filter theory in the modeling process. A new method is developed to calculate the biased error in the road direction with improved accuracy. In addition, the Kalman filter in the proposed map-matching algorithm filters the white noise error and corrects the biased error in both the cross-track and along-track directions. The research benefits the land vehicle navigation industry by providing an algorithm of improved accuracy and reliability.

GPS SIGNAL ERROR AND FUNDAMENTALS OF MAP-MATCHING

GPS Signal Error

The accuracy of the civilian GPS systems has been improved significantly since the U.S. government terminated the Selective Availability in May 2000. However, the accuracy of such systems is still subject to many factors such as the satellite ephemeris error, the satellite clock error, the ionospheric delay error, the tropospheric delay error, the multipath error, and the GPS receiver error (Bao and Liu, 2006).

The position information from a GPS signal is the most important factor used to identify the vehicle's exact location. The main component of the GPS location error, which is caused by the satellite ephemeris error, the satellite clock error, the ionospheric delay error, and the tropospheric delay error (Jun, Guensler, and Ogle, 2006), is relatively stable in the short term. This kind of stable error is called *bias error* or *slow drift error*. Alternatively, the error component from the multipath error and the receiver's hardware error is considered to be a random distribution, which is known as the *white noise error* (Kim et al., 2000). Considering the overall influence of these two errors, the GPS location error is biased but not a white Gaussian distribution that is assumed by current models.

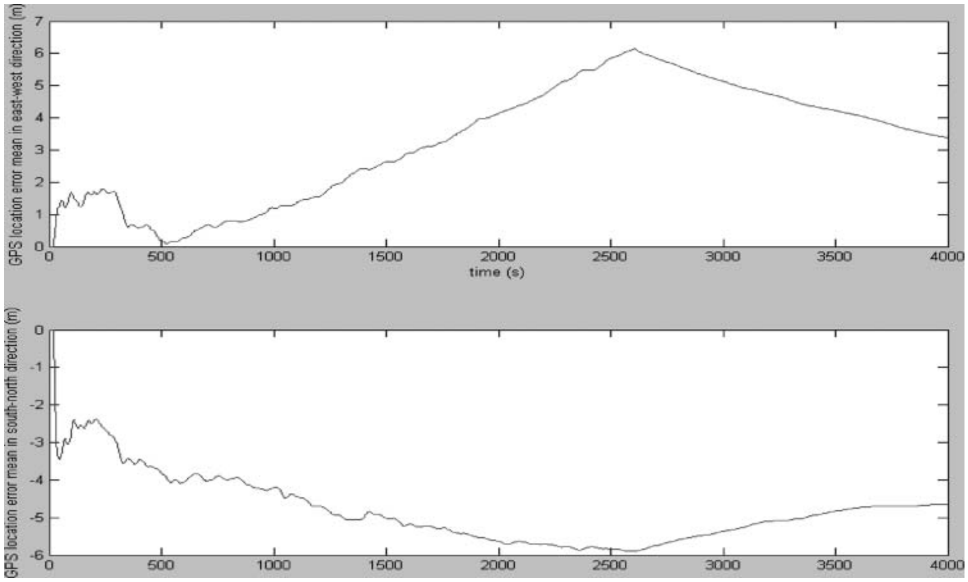

Figure 1 Mean global positioning system location error and time.

A distribution of the GPS location error observed from the field is shown in Figures 1 and 2. The data came from several experiments in an individual vehicle in the urban area of Shanghai, China, using a common commercial GPS receiver (Garmin GPS 18x Serial Receiver for PC). A total of above-10,000 position fixes were obtained. The map data, reference points, and the driving log were used to get the accurate position of the GPS tracks and the error. When recording the GPS fixes, particular attention was made to avoid making lane changes so that the lane information logged into the driving log remained consistent. Because the road map selected for the study is of high accuracy (the positions of 95% of the all intersections are within 1 m), the cross-road GPS error can be eliminated by using the location of the road's centerline, the information of the traveled lane, and the width of the lanes and roads. The reference points are the points whose accurate locations are known, such as the stop lines and the edge of intersections. When recording the GPS tracks, the GPS fixes at the reference points were marked by the recorder. The GPS error in the road direction was corrected in the laboratory by translating the along-road tracks according to the GPS fixes at reference points. In such a way, both the cross-road and along-road errors were reduced to a range of 0–1 m. Figure 1 depicts the error's mean in two directions as time elapses. The curve on the top represents the mean's value in an east-west direction, and the bottom curve represents the mean's component in a north-south direction. As can be seen, the GPS

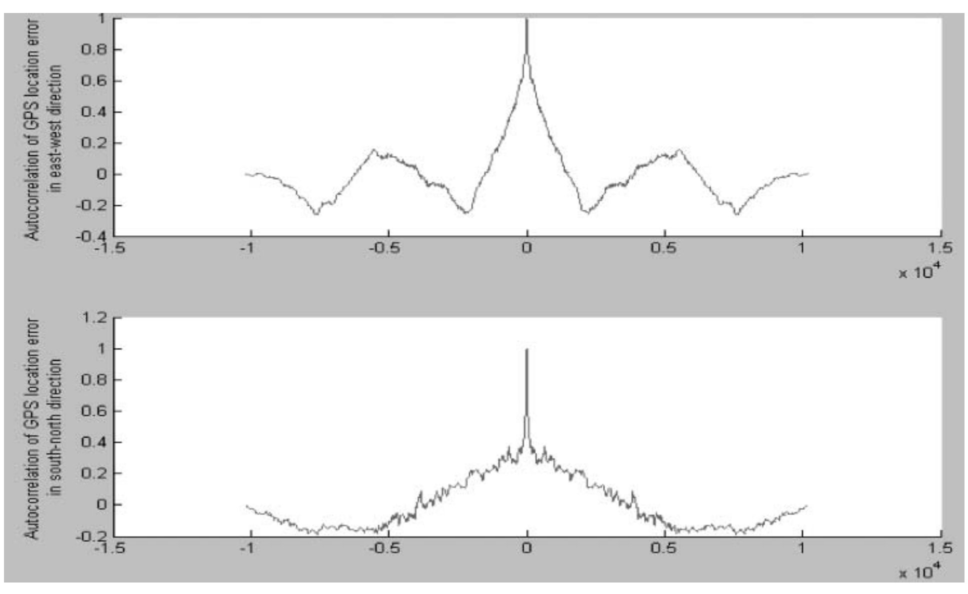

Figure 2 Autocorrelation function curves of global positioning system location error.

location error is a relatively stable value that changes slightly in the course of the vehicle's movement in the short term. Figure 2 is the autocorrelation of these two GPS error components. The curve on the top represents the autocorrelation of the error in an east-west direction, and the curve on the bottom represents the autocorrelation of the error in a north-south direction. The two curves are not impulse function graphics, which indicates that the GPS location error is not white noise.

Figures 1 and 2 show that directly using the GPS location information as the state observation is not proper because the noise of the GPS location information does not form a white Gaussian distribution. Hence, it is essential to develop a new state-space model in the Kalman filter to make the observation noises agree with the assumptions.

As previously mentioned, the GPS error is composed of the bias error and the white noise error, which can be expressed as follows:

$$e(k) = e\text{bias}(k) + e\text{white}(k)$$

where $e(k)$ is the GPS error at the time point k, ebias(k) and ewhite(k) is the component of the bias error and the white noise respectively. Because the bias error is relatively stable, i.e., $e$bias(T – 1) ≈ $e$bias(T), the deviation of the GPS error, Δe(T), can be expressed as follows:

$$\Delta e(T) \approx e\text{white}(T) - e\text{white}(\text{T} - 1)$$

It was verified by the field observation that the distribution of the error deviation at two adjacent time points is white with zero mean normal distribution. Figure 3 shows the changes in the mean of the error's deviation along with time. The curve on the top represents the change in an east-west direction, and the curve on the bottom represents the same information in a north-south direction.

The curves indicate that the mean of the deviation's components in the two directions is constantly zero, which verifies the assumption that the deviation has a zero mean distribution. Figure 4 shows the autocorrelation of the deviation between the adjacent GPS location errors in two vertical directions. The curve on the top represents the autocorrelation in an east-west direction, and the curve on the bottom represents the autocorrelation in a north-south direction. The curves in Figure 4 exhibit a similar shape to an impulse function graphic, which indicates that the deviation is white. Hence, the deviation's components in both directions follow the distribution of $N(0, R)$. Therefore, if the GPS location error at the last time point can be used as the observation at the current time point, it agrees very well with the assumptions of the Kalman filter theory.

Fundamentals of Map-Matching

The map-matching process is a specific procedure that reconciles a vehicle's location with the underlying map. The problem and the variables of interest are depicted in the following, in conjunction with Figure 5:

$g(k)$: the vehicle track point from GPS receiver;
$p(k)$: the actual corresponding location of $g(k)$ on the map road;
$e(k)$: the deviation between $g(k)$ and $p(k)$, $p(k) = g(k) - e(k)$;
$\bar{n}_i$ and $\bar{n}_j$: the intersection points of roads on the map, S_{ki} (i = 1, 2,. . .) are road arcs on the map;
$q(k)$: the nearest point from $g(k)$ on the arc S_{ki}, which is the intersection of the road arc S_{ki} and its vertical path through $g(k)$.

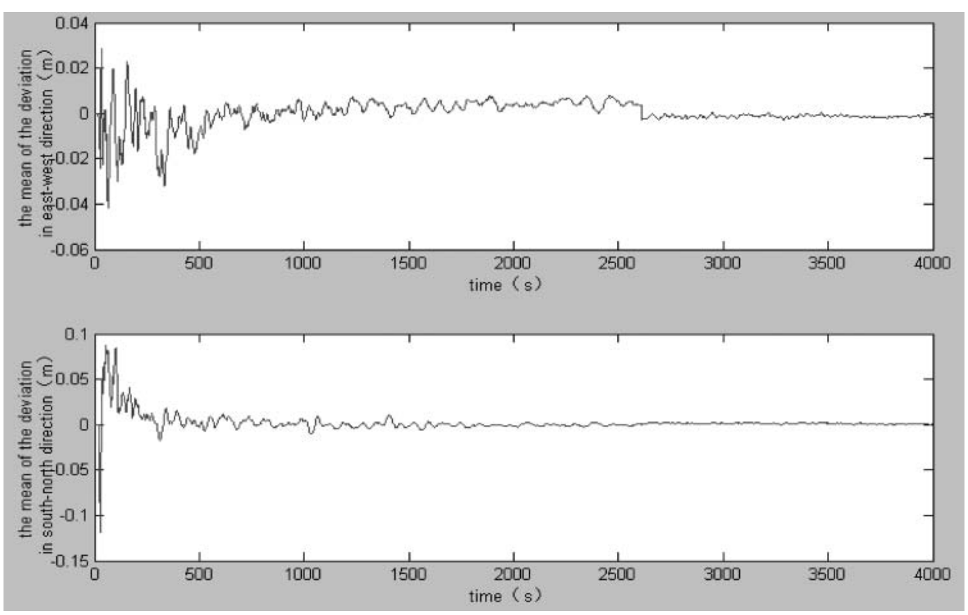

Figure 3 Mean deviation of global positioning system location errors in two directions and time.

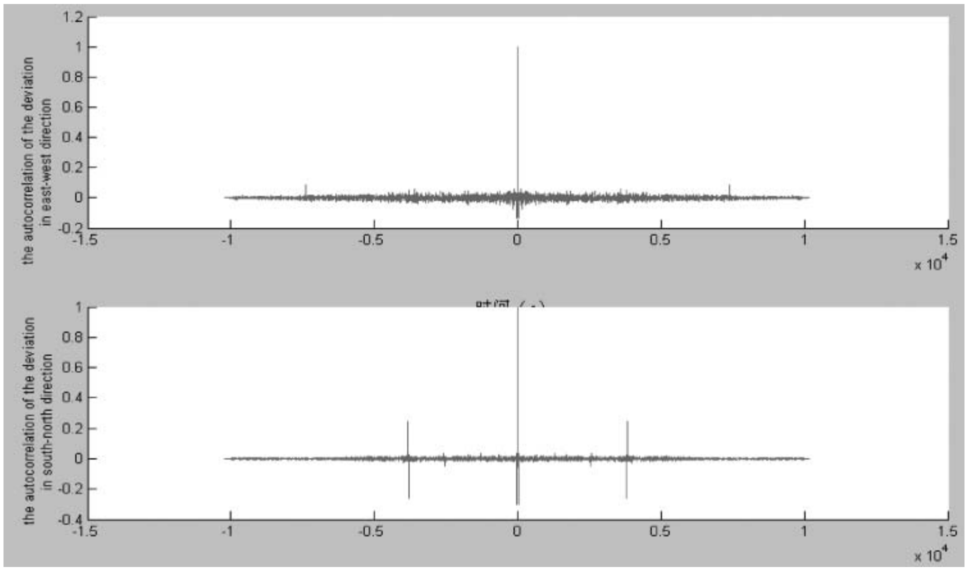

Figure 4 Autocorrelation of the deviation between adjacent global positioning system location errors.

There are two different ways to decompose $e(k)$ orthogonally: one is to decompose $e(k)$ in two directions, i.e., the road direction and the direction perpendicular to the road. The directions are denoted by $\vec{h}$ and $\vec{v}$ in Figure 5. The other is to decompose $e(k)$ in the north-south and the east-west directions, which are denoted by $\vec{x}$ and $\vec{y}$ in Figure 5. The two different decompositions can be expressed as follows:

$$e(k) = e_v(k)\vec{v} + e_h(k)\vec{h} \tag{1}$$

$$e(k) = \Delta Sn * \vec{y} + \Delta Se * \vec{x}$$

and

$$e_v(k)\vec{v} = q(k) - g(k) \tag{2}$$

$$e_h(k)\vec{h} = p(k) - q(k)$$

where $e_v(k) \in R$ is the error component perpendicular to the road, and $e_h(k) \in R$ is the component in the road direction. ΔSe and ΔSn are the error components in the direction of $\vec{x}$ and $\vec{y}$, respectively.

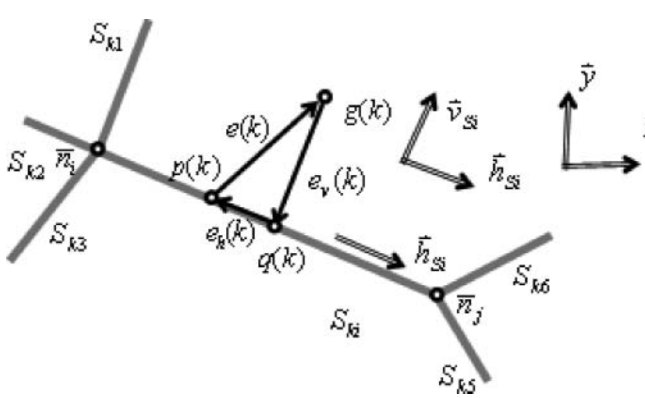

Figure 5 Procedure of map-matching.

Obtaining $e(k)$ is the premise of seeking $p(k)$. It is relatively easier to get the error component $e_v(k)$ by calculating the distance between $g(k)$ and $q(k)$, but how to obtain the component $e_h(k)$ is the major issue of concern. Indeed, obtaining this component is a common problem in existing map-matching algorithms and mishandling of this process often leads to inaccurate navigation devices.

THE PROPOSED KALMAN FILTER ALGORITHM

The New Kalman Filter Model

Because the noise from the GPS receivers does not meet the ideal requirements of the Kalman filter theory, the estimated locations are usually not accurate in the conventional models. As previously mentioned, if the GPS error at the previous time point can be used as the observation at the current time point, the noise, which is white with normal distribution, will agree nicely with the Kalman theory's assumptions. In the proposed algorithm, the GPS error in the two vertical directions are added into the state space model as state variables and their observed values are directly from the previous time point. The deviation of the error is decomposed into two parts along $\vec{x}$ and $\vec{y}$, which are $v_{\Delta Sn}$ and $v_{\Delta Se}$, respectively. Hence, the location observation can be expressed as follows:

$$z_{Sn}(k) - z_{\Delta Sn}(k) = S_n(k) + v_{\Delta Sn} \tag{3}$$

$$z_{Se}(k) - z_{\Delta Se}(k) = S_e(k) + v_{\Delta Se} \tag{4}$$

$z_{Sn}(k)$ and $z_{Se}(k)$ are the observation values of the GPS track location in the direction of $\vec{y}$ and $\vec{x}$ at time k, respectively. $z_{\Delta Sn}$ and $z_{\Delta Se}$ are the errors of the GPS tracks in the same directions at time k, which are equal to the component of $e(k-1)$ between the

GPS track's location $g(k-1)$ and the matched point $p(k-1)$ at the last time point in the direction of $\vec{y}$ and $\vec{x}$. $S_n(k)$ and $S_e(k)$ are the predicted location in the same direction at time k, respectively. The location observation noises are $v_{\Delta Sn}$ and $v_{\Delta Se}$, whose distribution agrees with$N(0,\ R_{\Delta Sv})$.

According to the previously mentioned analysis, the state space is designed to be $x = [S_n S_e V_n V_e \Delta S_n \Delta S_e]^T$. V_n is the component of the vehicle's velocity in the $\vec{y}$'s direction and V_e is the velocity's component in the $\vec{x}$'s direction. $\Delta Sn(k)$ and $\Delta Se(k)$ are the predicted GPS error in the same directions at time k, respectively. The predicting formula reads as follows:

$$x_k = Fx_{k-1} + w \tag{5}$$

$$F = \begin{bmatrix} 1 & 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad w = \begin{bmatrix} 0 \\ 0 \\ w_{vn} \\ w_{ve} \\ w_{\Delta Sn} \\ w_{\Delta Se} \end{bmatrix}$$

The observation vector is set as $z = [(z_{Sn} - z_{\Delta Sn})(z_{Se} - z_{\Delta Se}) z_{Vn} z_{Ve} z_{\Delta Sn} z_{\Delta Se}]^T$. The observation of z_{Sn} and z_{Se} are the components of the vehicle's location (from the GPS receiver) in the directions of $\vec{y}$ and $\vec{x}$, while z_{Vn} and z_{Ve} are the components of the vehicle's velocity. Therefore, the observation model can be expressed as follows:

$$z_k = Hx_k + v \tag{6}$$

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad v = \begin{bmatrix} v_{\Delta Sn} \\ v_{\Delta Se} \\ v_{vn} \\ v_{ve} \\ v_{\Delta Sn} \\ v_{\Delta Se} \end{bmatrix}$$

The position of $p(k)$ is obtained by vertically mapping the estimated location from $S_n(k)$ and $S_e(k)$ onto the nearest arc. In the process of designating the new state-space model and the observation model, $e(k-1)$, i.e., the difference between $g(k-1)$ and $p(k-1)$ plays an important role in finding $p(k-1)$, whereas $e(k-1)$ is used as the current observation value. Therefore, both the error component in the cross-road direction and the component in the road direction need to be sought accurately. The detailed method is presented in the next section.

The Proposed Method for Correction of State Variables and Noise Variances

Finding $z_{\Delta Sn}$ and $z_{\Delta Se}$ from an accurate $e(k-1)$ is essential to the problem. Because there is not enough historical track information at the beginning stage of map-matching, the mapped point can only be obtained by mapping the GPS track point onto the nearest road vertically without any precorrection. As a result, the calculated $e(k)$ includes only the component of $e_v(k)$ in the cross-road direction but missing the information of the component $e_h(k)$ in the road direction. This $e(k)$ cannot give the accurate error information about the following track points. This problem is solved by the method subsequently presented.

According to the analyses of the difference between the adjacent GPS errors, the mean of GPS error before and after the vehicle's turning movement is very close, as Figure 1 shows. If $\bar{m}_{last}$ and $\bar{m}_{current}$ are used to denote the mean of the GPS error on the previous road arc and current road arc, then

$$\bar{m}_{last} \approx \bar{m}_{current} \tag{7}$$

It is relatively easier to obtain the cross-road component of $\bar{m}_{last}$, namely, $\bar{m}_{v-last}$ and the cross-road component of $\bar{m}_{current}$, namely, $\bar{m}_{v-current}$, which is shown in Figure 6. To obtain a more accurate result on a real-time basis, this calculation needs to be conducted when there are already C_{eff} track points mapped onto the current road arc, rather than when the vehicle just finishes turning and moves to the next road arc. C_{eff} is the number of GPS fixes defined in order to obtain an accurate $\bar{m}_{v-current}$, (5 in the experiments). Thus, $\bar{m}_{v-current}$ is calculated from the C_{eff} track points. $\bar{m}_{h-last}$ and $\bar{m}_{h-current}$ are denoted as the components of the error's mean in the road direction, corresponding to $\bar{m}_{last}$ and $\bar{m}_{current}$. α is the angle between the intersecting roads.

According to the geometric analyses conceptualized on the upper left corner of Figure 6, $\bar{m}_{current}$ can be orthogonally decomposed into two directions along$\bar{m}_{v-last}$ and $\bar{m}_{h-last}$, which are

$$\bar{m}_{v-last} \approx \bar{m}_{v-current} \cos\alpha + \bar{m}_{h-current} \sin\alpha \tag{8}$$

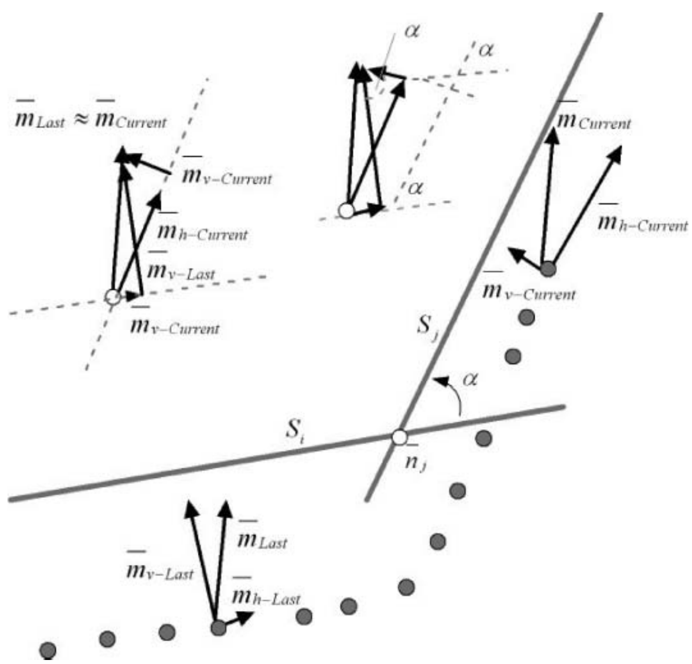

Figure 6 Conceptual illustration of error calculation by using global positioning system tracks near a turning.

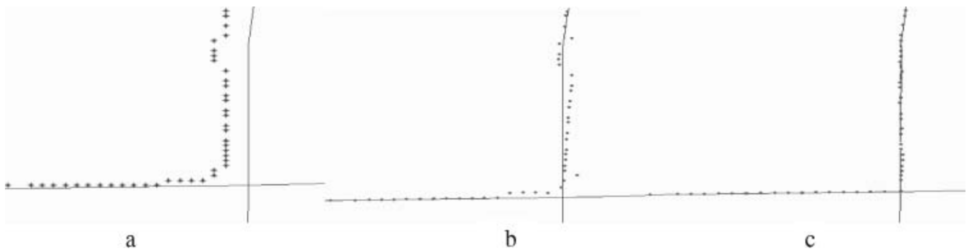

Figure 7 The raw tracks, precorrected tracks, and final map-matching results.

$$\bar{m}_{h-last} \approx \bar{m}_{h-current} \cos\alpha + \bar{m}_{v-current} \sin\alpha \quad (9)$$

The relation between $\bar{m}_{h-current}$, $\bar{m}_{v-last}$, and $\bar{m}_{v-current}$ can be derived, which reads as follows:

$$\bar{m}_{h-current} \approx [\bar{m}_{v-last} - \bar{m}_{v-current} \cos\ \alpha] \big/ \sin\alpha \quad (10)$$

To ensure that the truncation error from calculation will not affect the accuracy, this process is applied only in the cases in which the turning angle is larger than 15°. The mean of the along-road GPS error, $\bar{m}_{h-current}$, is used to replace the current value to calculate the current GPS error $e(k)$ and identify the mapped point $p(k)$ on the corresponding road. Furthermore, the observations of $z_{\Delta Sn}$ and $z_{\Delta Se}$ at the next time point can be obtained at the same time. Because of the correction to $e(k)$, the other variables in the state space need to be updated synchronously for consistency. The posteriori state estimates ΔSn and ΔSe are updated by $z_{\Delta Sn}$ and $z_{\Delta Se}$ and at the same time, $S_n(k)$ and $S_e(k)$ are updated along the y axis and the x axis according to the mapped point $p(k)$. The error variance matrix of the posteriori state $P_{k|k}$(six-dimensional) is updated with the variance $P_{\Delta Sn}$ and $P_{\Delta Se}$ of the error differences in the adjacent GPS track pairs:

$$P_{k|k}(1,1) = P_{k|k}(5,5) = P_{\Delta Sn} \quad (11)$$

$$P_{k|k}(2,2) = P_{k|k}(6,6) = P_{\Delta Se}$$

The along-road GPS error of the following track points are corrected effectively with the mean $\bar{m}_{h-current}$ by the proposed Kalman filter approach. After the correction, the GPS error in the road direction is white with normal distribution whose mean is zero, which can be handled easily by the Kalman filter. In the process of vehicle navigation, the method is used to update the state of the Kalman filter after vehicles make turns. Thus, after the initial stage of navigation process, the error component $e_h(k)$ in the road direction is corrected. Although the importance of $e_h(k)$ for identifying the mapped point $p(k)$ is well recognized by many researchers, it has not been addressed in sufficient detail in the literature. The discovery of $e_h(k)$ is one of the main contributions of the proposed approach.

APPLICATION AND RESULTS

The proposed Kalman filter algorithm is one of the four primary elements of the integral navigation system, which was designed to improve the accuracy of the GPS's fix location (in both the along-road and cross-road directions). The other major components of the system include a computerized digital map creation algorithm that generates digital road networks from various resources (e.g., paper maps); a nonlinear map adjusting algorithm that automatically corrects map errors during the extracting process; and a so-called virtual differential algorithm that performs road identification during the map-matching process.

In the system, the virtual differential approach (Liu, Xu, Norville, and Bao, 2008) identifies the corresponding road arc of $\hat{p}(k)$ with the information of the historical matching results, the vehicle's velocity and direction, and the topological structure of the map. The Kalman filter serves as a preprocessing tool to correct the GPS errors before mapping the point onto the identified road arc to get the matched point $p(k)$. In this section, the authors present a set of results from the experimental studies to demonstrate the effectiveness of the proposed Kalman filter algorithm. Focuses are placed on examining the performance of map-matching algorithms with and without the precorrection process.

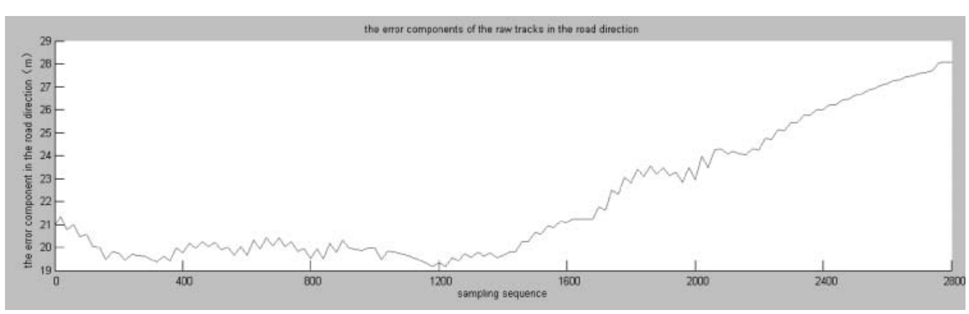

Figure 8 The error of raw global positioning system track locations in the road direction.

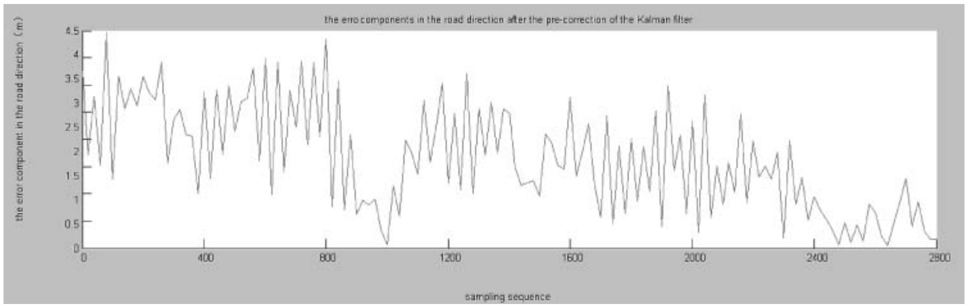

Figure 9 The along-track error of precorrected global positioning system track locations.

Figure 10 Raw and matched global positioning system tracks for a large area.

The prototype navigation system was tested in Shanghai and Hefei, two metropolitan cities in China. A data set composed of the accurate location of the recorded GPS tracks was first created by using the accurate map data, accurate reference points and the driving log. Then, the data set was used to compare with the results obtained from the map-matching algorithm. The number of GPS track points recorded was around 35,000, and the majority of the data were collected continuously. As depicted in the following paragraph, the results from the experimental study show that the algorithm works reasonably well in correcting the GPS error and improving the accuracy of map-matching.

Figure 7a shows the raw track points obtained from an in-vehicle GPS receiver. It indicates that the GPS locations have an error with non-zero mean because the track points have relatively unified deviation from the road map. Figure 7b shows the corrected tracks by the Kalman filter. By comparing Figure 7a and Figure 7b, one can observe that the improved Kalman filter can correct not only the GPS location error in the direction perpendicular to the road but also the error in the road direction. The error correction process in the road direction improves the accuracy of the GPS navigation system significantly, especially at the places near intersections. Figure 7c is the final map-matching result after the precorrection process, which is obtained by vertically mapping the corrected track points onto the corresponding roads.

In the experimental study, we recorded the precorrected locations of the raw track data. We investigated further by comparing the statistics of the distances between the raw track points and their correct positions, and the distances of the precorrected locations to the corresponding correct positions. The along-road error of the raw GPS track locations and the corrected GPS track locations are shown in Figure 8 and Figure 9, respectively. It is worthy to note that the results presented in Figure 9 were obtained after the initial stage of navigation. At the beginning stage, the algorithm failed to get a desired result in lack of enough track information. By comparing the two figures, one

Table 1 Comparison of the along-track error of the raw tracks and precorrected tracks.

Along-Track Error	Min (m)	Max (m)	*M* (m)	*SD*
Raw tracks	19.1	28.3	21.7	3.625
Precorrected tracks	0.1	4.5	1.6	1.505

m-meter.

Table 2 Comparison of the algorithms with and without precorrection.

Algorithms	Total Number of Track Points	Number of Track Points Near Intersections	Number of Misused Track Points
With Precorrection	35,000	3,927	162
Without Precorrection	35,000	3,927	523

can observe clearly the new algorithm's effectiveness in error correction along the road direction.

The statistics of the along-road error are presented also in Table 1. The precorrected tracks in Table 1 demonstrates those tracks that were corrected by the improved Kalman filter. Table 2 shows a comparison between the algorithms with and without the precorrection process in terms of the number of track points that were misused or treated improperly in the map-matching process. The algorithm without the Kalman filter uses directly the information of vehicle's direction, speed, the historical matched road, and the topological structure of the map in map-matching. The major difference between these two algorithms is that the one without the precorrection treatment cannot effectively handle the GPS error along the road direction. Figure 10 shows a complete result obtained from a large portion of Hefei's network.

CONCLUSIONS

In this article, we analyzed the statistic properties of the GPS location error and developed an improved Kalman filter approach for preprocessing the GPS data in map-matching. We conducted field observations and used the observed data to verify that the GPS error is composed of the bias error and the white noise error. We investigated the difference of the GPS location errors at two adjacent time points and its noise. According to the analyses, the components of the GPS error along two vertical directions were added into the state space as state variables to develop an improved Kalman filter model. At the same time, the GPS error in the road direction was obtained by using the vehicle tracks and the information after the vehicle makes turns. The combination of the improved Kalman filter and the method seeking for the along-track GPS error makes the new algorithm advantageous in effectively dealing with both the bias error and the white noise error, not only in the road direction but also in the direction perpendicular to the road. We then examined the effectiveness of the model by experimental studies. The findings of this research contribute to development of accurate and reliable in-vehicle navigation systems.

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