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A vehicular positioning with GPS/IMU using adaptive control of filter noise covariance☆

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Graphical abstract

Abstract

Vehicular positioning with GPS/IMU has been studied a lot to increase positioning accuracy. The positioning algorithms mainly use DR (Dead Reckoning) which uses EKF (Extended Kalman Filter). It is basic and very important core technology in positioning section. However, EKF has a major drawback in that it is impossible to make very accurate system and measurement models for a real environment. In this work, we propose an algorithm to estimate vehicle's position as distribution form, and to control the system and measurement noise covariance to compensate for this major disadvantage. The proposed method to control noise covariance is independently processed, using fading factor and sensor error while considering the driving condition.

Keywords: GPS; IMU; Extended Kalman Filter; System/measurement noise covariance; Vehicular positioning

1. Introduction

Nowadays autonomous vehicle and C-ITS (Cooperative Intelligent Transportation System) are to be in the limelight. They are very essential and active in developing. In order to realize perfect autonomous vehicle and C-ITS, information of the present vehicle's position is very important because provide any service of them [1]. The common way to generate information of vehicle's position is to use GPS [2]. There is already a large amount of research and development regarding positioning with GPS. However, it is difficult to calculate the position in real-time because there are many obstacles with regard to accurate and reliable positioning [3]. For example, it is impossible to obtain accurate positioning in a tunnel or under an overpass, as well as between skyscrapers. GPS also has low operating

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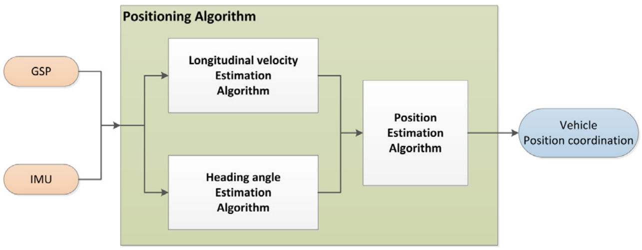

Fig. 1. Block diagram of the proposed algorithm for vehicular positioning.

frequency and sensor errors, so it is impossible to measure the position accurately. That being said, technologies estimating vehicle position under 1 m accuracy are necessary to realize autonomous vehicle and C-ITS. That is why many methods are developed to get around the limits of GPS vehicular positioning such as DR (Dead Reckoning), radar, laser, vision sensor, map matching, etc. Among them, DR with GPS and IMU [Inertial Measurement Unit] is core method for the vehicular positioning. EKF (Extended Kalman Filter) is commonly used in DR as an estimating method [4]. But it has a critical disadvantage for being used as an estimation, in that the performance of EKF is dependent on how accurate system and measurement models are. If the theoretical behavior of the filter and its actual behavior do not agree, divergence and low accurate output tend to occur [5].

In this paper, the algorithm for solving the critical disadvantage of DR with GPS and IMU is proposed. This algorithm is a basic technique used for vehicular positioning. The algorithm that assumes vehicular positioning via EKF is of a distribution form and it adaptively controls the EKF noise covariance. The system and measurement noise covariance are independently controlled, and so more reliable and accurate positioning is possible. In Section 1, we explain entire vehicular positioning algorithm. In Section 2, we introduce the algorithm for how to control system and measurement noise covariance that are appropriate for the positioning of the driving vehicle in urban environment. The test and result of the algorithm proposed are discussed in Section 3 [6,7]. Finally, we conclude the paper in Section 4.

2. Vehicular positioning algorithm

The proposed vehicular positioning algorithm uses GPS, IMU and is made up of three parts as distribution structure forms: longitudinal velocity, heading angle, position estimation as seen in Fig. 1. The distribution algorithm makes it easier to model, provides less load, and is more flexible with other system compared to a single structure form. Each estimation algorithm uses EKF in order to estimate longitudinal velocity, heading, and position coordinates. GPS data is used in measurement model of the filters, and IMU mainly is used as one of data in system model. The discrete-time EKF for GPS, IMU navigation is summarized as follow.

(1) Start with the initialized state vector and state covariance matrix: $\hat{x}_0, \hat{\hat{P}}_0$.

(2) Calculate the Kalman gain matrix:
$$K_k = P_k^- H^T \left(H P_k^- H^T + R\right)^{-1}.$$

(3) Calculate the update state vector:
$$\hat{x}_k = \hat{x}_k^- + K_k \left(z_k - H\hat{x}_k^-\right).$$

(4) Update the error covariance matrix:
$$P_k = P_k^- - K_k H P_k^-.$$

(5) Predict the new state vector, state covariance matrix:
$$\hat{x}_k^- = f\left(\hat{x}_{k-1}\right), \qquad P_k^- = \left(F_{k-1} P_{k-1} F_{k-1}^T\right) \cdot \lambda + Q.$$

The system and measurement model for estimation of longitudinal velocity, heading angle, position are defined by Eqs. (1)–(6). Eqs. (1), (2) are system, measurement model for longitudinal velocity and Eqs. (3), (4) are for heading angle and Eqs. (5), (6) are for estimating position. The final values $\hat{X}_k^-$, $\hat{Y}_k^-$ are vehicle's position that are estimated as longitude and latitude.

$$\hat{x}_k^- = \begin{bmatrix} (V_{Long}^-)_k \\ (a_{Long}^-)_k \\ \theta_k^- \end{bmatrix} = \begin{bmatrix} (V_{Long}^-)_{k-1} + \Delta t \cdot (a_{Long}^-)_k \\ (ACC_x - g \cdot \sin\theta_{k-1}^-) \cdot \cos\theta_{k-1}^- \\ \theta_{k-1}^- + \Delta t \cdot (GYRO_y)_k \end{bmatrix} \tag{1}$$

$$z_k = \begin{bmatrix} (V_{GPS})_k \\ (\dot{V}_{GPS})_k \\ \left(\tan^{-1}\dfrac{V_Z}{V_{XY}}\right)_k \end{bmatrix} \tag{2}$$

$$\hat{x}_k^- = \left[\hat{\psi}_k^-\right] = \left[\hat{\psi}_{k-1} + \Delta t \cdot (GYRO_z)_k\right] \tag{3}$$

$$z_k = \left[(\psi_{GPS})_k\right] \tag{4}$$

$$\hat{x}_k^- = \begin{bmatrix} \hat{X}_k^- \\ \hat{Y}_k^- \end{bmatrix} = \begin{bmatrix} \hat{X}_{k-1} + \Delta t \cdot (V_{Long}^-)_k \cdot \cos\hat{\psi}_k^- \\ \hat{Y}_{k-1} + \Delta t \cdot (V_{Long}^-)_k \cdot \sin\hat{\psi}_k^- \end{bmatrix} \tag{5}$$

$$z_k = \begin{bmatrix} (X_{GPS})_k \\ (Y_{GPS})_k \end{bmatrix} \tag{6}$$

where θ is pitch angle, $GYRO_y$ and $GYRO_z$ are y and z-axis angular velocity, ACC_x is x-axis acceleration, g is acceleration of gravity, a_{Long} and V_{Long} are the longitudinal acceleration and velocity, V_{GPS} and ψ_{GPS} and X_{GPS} and Y_{GPS} are velocity and yaw and longitude and latitude from NMEA of GPS data, V_Z and V_{XY} is velocity calculated by variation of altitude and longitude and latitude, respectively.

3. Adaptive control of filter noise covariance

It is very difficult to estimate the position of a running vehicle using only the algorithm mentioned above when in a downtown environment. This is because signals from the GPS are very vulnerable to multi-path or GPS outage and system models in the filter are not perfect in a real driving environment. As a result, the original EKF depends on how accurate the system models made in the filter are. However, it is impossible to accurately model, so the process noise covariance **Q** and measurement noise covariance **R** should be adjusted via tuning. Tuning **Q** and **R** plays an important role in determining the Kalman Gain, influencing the performance of the filter.

3.1. The control of system noise covariance

The system noise covariance, **Q** should be adjusted by the filter algorithm, as there is no way to control it directly. One method to control **Q** in an adaptive way is to use fading factor. The method using fading factor is on the calculation of the scale factor. It is to apply a factor matrix to the predicted covariance matrix to deliberately increase the variance of the predicted state vector. The variance of predicted state vector in the step (4) of the EKF process is mentioned in Section 2 and it is adjusted as Eq. (7).

$$(P_A)_k^- = \lambda P_k^- = \lambda(A_{k-1}P_{k-1}A_{k-1}^T + Q_k) \tag{7}$$

λ is a fading factor and is updated in each epoch by considering EKF control parameters: C_{v_k} (Covariance matrix of Innovation Sequence), $\hat{C}_{v_k}$ (Statistical Sample Estimate of C_{v_k}). The fading factor is defined by Eq. (8).

$$\lambda = \max(1, tr(\hat{C}_{v_k})/tr(C_{v_k})) \tag{8}$$

[$tr(\cdot)$ is the trace of matrix]

C_{v_k}, $\hat{C}_{v_k}$ are calculated by Eqs. (9), (10)

$$C_{v_k} = H_k P_k^- H_k^T + R_k \tag{9}$$

$$\hat{C}_{v_k} = \frac{1}{N-1}\sum_{j=j_0}^{k} v_j v_j^T \tag{10}$$

where N is the window size chosen inductively, v_j (Innovation Sequence) and j_0 are given by Eqs. (11) and (12).

$$v_k = z_k - \bar{z}_k = z_k - H\hat{x}_k^- \tag{11}$$

$$j_0 = k - N + 1. \tag{12}$$

When $\lambda > 1$, it means the filtering tends to be unstable. Conversely, the filtering is in a steady state when $\lambda \leq 1$. The new variance of the predicted state vector $(P_A)_k^-$ adjusts system noise covariance indirectly and increases tracking performance for the vehicle positioning by λ.

3.2. The control of measurement noise covariance

The proper operation of the process noise covariance **Q** scaling method depends on the proper measurement noise covariance **R** setting. **R** can be directly adjusted for real driving situation by using sensor. In the vehicular positioning algorithm proposed, GPS is used as measurement value in estimation filter, EKF. Measurement noise which is GPS noise in driving vehicle includes bias of sensor itself and degree of reliability of GPS signal in urban driving conditions. The urban driving condition is divided into driving environments such as Multi-path, GPS outage and driving state such as Stop, Forward driving, Curve, etc. Therefore, measurement noise covariance matrix in the proposed vehicular positioning filter is expressed by Eq. (13).

$$\mathbf{R} = \mathrm{diag}[K\cdot\sigma_1^2(1+\rho),\ K\cdot\sigma_2^2(1+\rho), \ldots, K\cdot\sigma_n^2(1+\rho)] \tag{13}$$

diag in Eq. (13) is diagonal matrix. This means each measurement value used for estimating the position is independent of others and has different noise term. σ_n is the bias of sensor itself, about nth measurement value, in estimating filter. ρ is the degree of reliability of GPS signal in an urban driving environments, which are applied with same amount of noise in each measurement value term. **K** is the gain that **R** matches **Q** up by inductively scaling.

•The bias of sensor itself

The sensor mentioned in this paper is GPS receiver. In order to measure the bias of sensor itself for measurement noise covariance, GPS activates in stop state to output the measurements that the output of the system is held constant. In this case, only the bias of sensor itself remains because the original data is subtracted. The equation for calculating the bias of sensor itself is σ_n^2, which is noise standard variance and is expressed by Eq. (14).

$$\sigma_n^2 = \frac{\sum_{i=1}^{k}\left((\varepsilon_n)_i - \mu_n\right)^2}{k} \tag{14}$$

where k is number of sampling data, $(\varepsilon_n)_i$ is noise error of nth measurement value in epoch i, μ_n is the mean of ε_n. The $(\varepsilon_n)_i$ is defined by Eq. (15).

$$(\varepsilon_n)_i = |(x_n)_i - (y_n)_i|. \tag{15}$$

Here, $(x_n)_i$ is GPS output of nth measurement value in epoch i and $(y_n)_i$ is the real value of nth measurement value in epoch i. The forms of x_n and y_n are different and have their own values, according to measurement: pitch, longitudinal acceleration, longitudinal velocity, yaw, longitude, latitude.

•The degree of reliability of GPS signal

The degree of reliability of the GPS signal ρ plays a very important role in increasing performance of vehicular positioning, because vehicles frequently drive under environments which have a low reliability of GPS. The algorithm that calculates ρ consists of two parts: a decision on driving environment ρ_E and a decision on driving state ρ_S. Thus, the reliability of GPS signal ρ is given by Eq. (16).

$$\rho = \rho_E \cdot \rho_S. \tag{16}$$

The algorithm used for the decision of the driving environment provides a way to determine the reliability of the GPS receiver in a driving vehicle with NMEA [The National Marine Electronics Association] sub data. These data are Quality indicator and number of visual satellites in GPGGA (Global Positioning System Fix Data), Fix and HDOP in GPGSA (Satellites Status), distance between GPS 2EA. The algorithm quantifies the quality of GPS data by using quality indicator, number of visual satellites, fix, HDOP, distance. ×0.1 is for quantifying GPS reliability in more detail. The parameters take values in the range of 0, 1.1 ∼ 10.0 and indicate higher quality as the values approach 10.00. 0 tells GPS cannot be used for positioning. The way these parameters are quantified is described in Fig. 2.

Among these factors, 'Relative distance between GPS 2EA' represents the reliability of the measurements of the GPS by

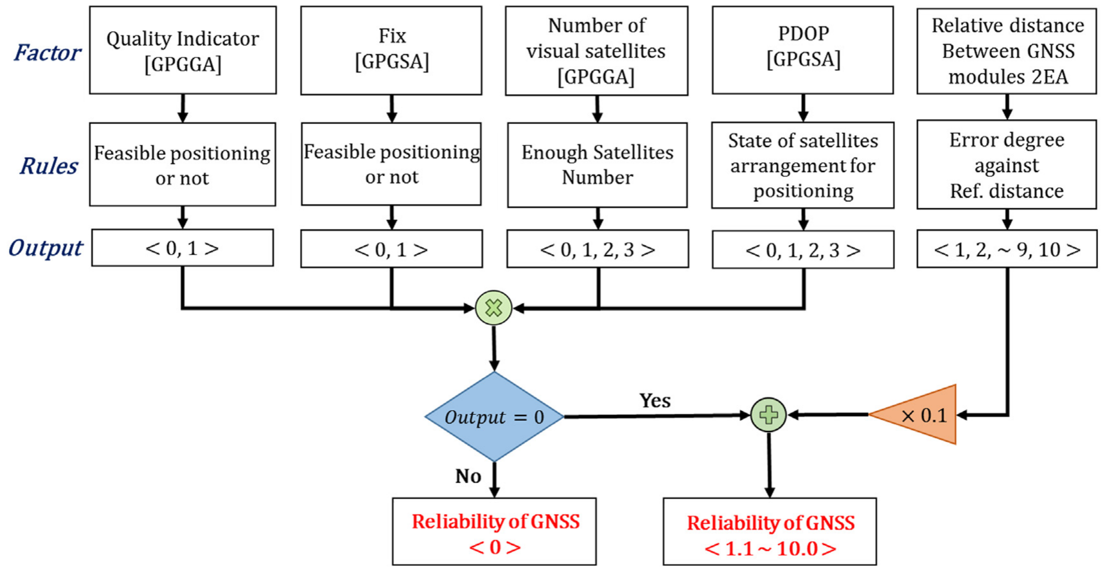

Fig. 2. Block diagram of algorithm for decision on driving environment.

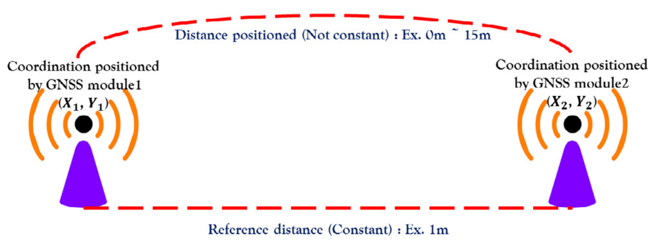

Fig. 3. The concept of measuring GPS reliability by relative distance.

Table 1
Driving mode for decision on driving state.

Mode	Condition
Straight running	$\lvert GYRO_z \rvert < \Theta$
Curve running	$\lvert GYRO_z \rvert \geq \Theta$
No move	$GPS_{vel} \cong 0$
Quick start	$\lvert GPS_{vel} \rvert < \alpha,\ ACC_x > \beta$
Quick braking	$\lvert GPS_{vel} \rvert < \alpha,\ ACC_x < -\beta$

using two GPSs. The two GPSs are positioned in a straight line and installed on the car-top at constant intervals. When position coordination is given by two GPSs, it is possible to calculate the distance between two GPSs using position coordinate. The positioned distance is calculated by longitudes and latitudes of two GPSs. Thus, the distance is compared with constant interval which is reference, then the difference between real distance and the positioned distance is quantified to measure GPS reliability as Fig. 3.

Using 5 factor, the algorithm is processed as Fig. 2. As a result, value of the algorithm, 0 indicates that GPS data cannot be used and 1.1 $\sim$ 10.0 indicate how reliable GPS data is. Finally, these are transformed into ρ_E which ranges from 9.9 to 1 and 11 for measurement noise covariance as Eq. (17).

$$\rho_E(x) = 11 - x. \tag{17}$$

The algorithm used for the decision on driving state is determined according to the driving modes of vehicle. The driving mode can be categorized into 5 modes: Straight running, Curve running, No moving, Quick start, Quick braking. The method used to decide which mode the driving vehicles is in during a real-time analysis is shown in Table 1.

Table 1 uses z as angular velocity *GYRO*, x as acceleration ACC_x, velocity from NMEA GPS_{vel} in order to determine modes of vehicle. Θ is threshold of angular velocity to decide whether it turn or not; α is threshold of velocity from GPS, which is very near zero; and β is the threshold of the acceleration, which is quite large. These mode are used in the estimation algorithm for determining the vehicular heading angle and the longitudinal velocity, because GPSs used in measurement models have relative performance in these states as compared with IMU which is used in system models. That is why the algorithm for the decision on driving state can determine when the weight of GPS is increased rather than the weight of IMU in the estimation filter. The rule for determining weight is below and uses Fuzzy ***IF-THEN*** rules for the logic [8].

(a) ***IF*** Straight running in estimation of heading angle ***THEN*** GPS is more reliable than IMU.
(b) ***IF*** Curve running in estimation of heading angle ***THEN*** GPS is less reliable than IMU.
(c) ***IF*** No moving in estimation of longitudinal velocity ***THEN*** GPS is more reliable than IMU.
(d) ***IF*** Quick start/Quick braking in estimation of longitudinal velocity ***THEN*** GPS is less reliable than IMU.

According to the Fuzzy ***IF-THEN*** rules, a parameter ρ_S of the decision on driving state has a value of 0.5 when GPS is more reliable than IMU. On the other hand, the parameter ρ_S has a value of 2 when GPS is less reliable and value 1 means nothing involved.

4. Experimental results

To verify the performance of the proposed algorithm, the algorithm has been tested on KIA K7 with GPS receivers [2EA]

Fig. 4. The setup of environment in vehicle test.

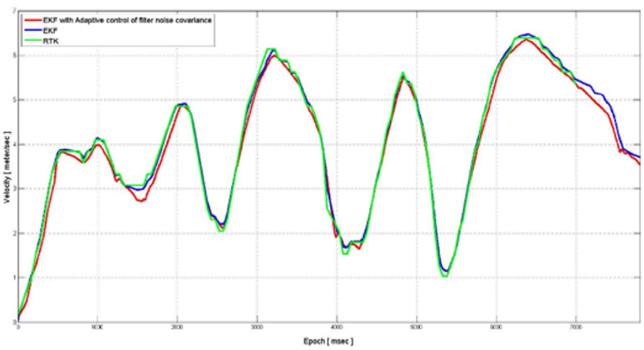

Fig. 5. The comparison of longitudinal velocity estimated.

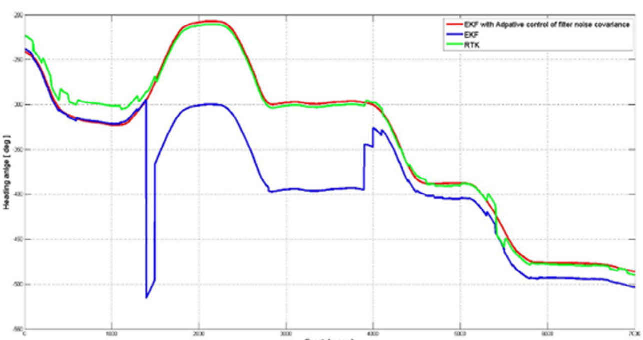

Fig. 6. The comparison of heading angle estimated.

and IMU [1EA]. The GPS receiver used in the experiments is U-blox 7p model which has 2.5 CEP accuracy and 1 Hz update rate. The IMU model is Mysen-M which has 4 g, 4 deg RMS range and 100 Hz update rate. The setup and environment of the test, which were conducted numerous times, are described in Fig. 4.

The tests are conducted in urban area where there are many buildings along the narrow path. The results of the tests are shown by the estimated values: longitudinal velocity, heading angle, coordinates and parameters for adaptive control of filter noise. The comparison results of the estimated longitudinal velocity between EKF and EKF with adaptive control filter noise and RTK as reference which is more reliable than other data, are shown in Fig. 5, and the estimated headings are in Fig. 6. The adaptive control method is smoother and catch the sudden splashed part of GPS for more reliable estimation. The factors making the result as Figs. 5, 6 are depicted in Fig. 7. The measurement noise covariance **R** is changed by the driving conditions as Fig. 7(a) and system noise covariance **Q** is differently fixed in both estimation parts. In order to control **Q** in a roundabout way, Lamda λ in Fig. 7(b), which controls

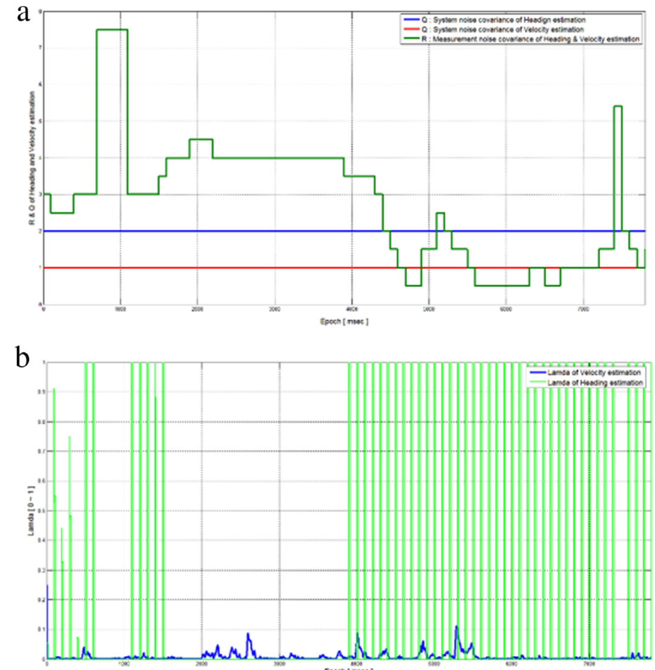

Fig. 7. The change of **Q** & **R** (7(a)), Lamda λ (7(b)).

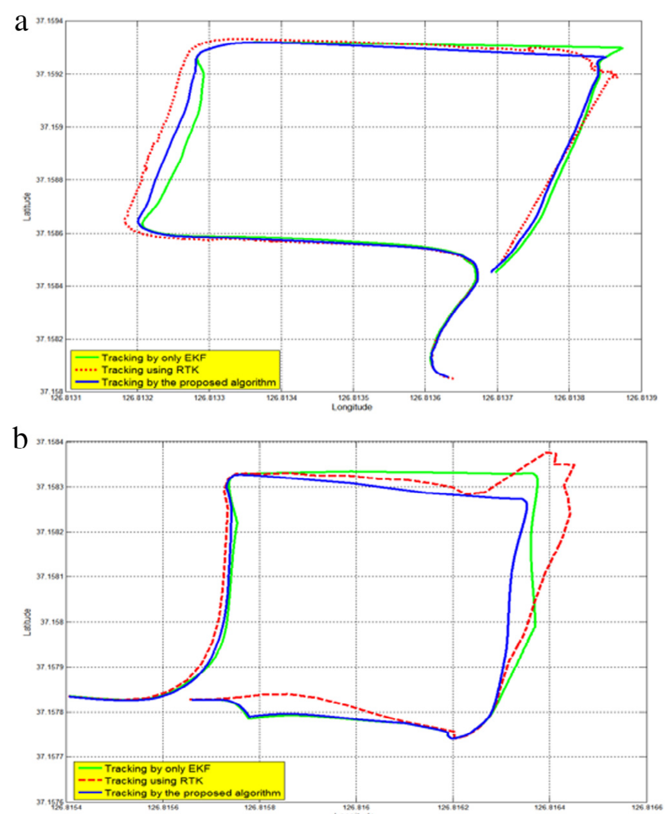

Fig. 8. The coordination estimated of vehicle in the low-multipath (8(a)) and high-multipath environment (8(b)).

the predicted state $(P_A)_k^-$ for estimation of heading, fluctuates more than one for estimation of longitudinal velocity.

The final result, coordination is shown as Fig. 8. Fig. 8(a) is the coordination in low-multipath environment with the result of EKF, Adaptive control method, high-cost RTK which has great performance as reference. Fig. 8(b) is in high-multipath environment with EKF, RTK for verifying performance of the proposed method. The result of the proposed method has good tracking ability because of Adaptive DR, even though the result of RTK quite bounce under lots of GPS signal blocked. In low multipath environment where RTK is less influenced by blocking signal, an average error and RMS 1σ error of EKF compared with RTK as reference, are 2.069 m and 2.135 m 1σ. On the other hand, an average error and RMS 1σ error of the proposed method are just 1.59 m and 1.63 m 1σ, which are lower than EKF.

5. Conclusion

In this paper, we proposed the method controlling EKF filter noise covariance which consisted of system and measurement noise covariance. They are independently, automatically adjusted by many factors. A system noise covariance **Q** indirectly influences the performance of system model in EKF by using Lamda λ. A measurement noise covariance **R** is adjusted by the driving conditions: the driving environments, the driving state. The result of positioning by using the proposed method is more reliable and accurate than only using EKF. In special situation, the performance of the proposed method is even better than the expensive instrument using high-cost RTK. In low-multipath area where RTK has quite good performance, the performance of the proposed algorithm is around 0.4 m better than one using only EKF.

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