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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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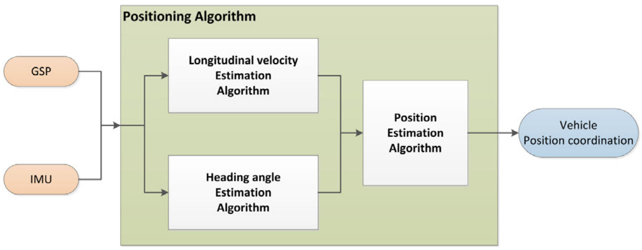

Fig. 1. Block diagram of the proposed algorithm for vehicular positioning.

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.

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

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

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

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

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

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

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.