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Multi-Rate Sensor Fusion Localization Algorithm using Camera and GPS in Urban Environments

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Executive Summary

Interest in autonomous vehicles is increasing, and many related studies are being conducted. However among them, the localization of autonomous vehicles is essential for generating and controlling vehicle routes. Recently, studies have been conducted to estimate the location of a vehicle using various sensors. However, as various sensors are used, various output cycles and data delay problems of each sensor must be solved. This paper proposes a localization algorithm in an urban environment using an inertial sensor, GPS, camera, and a high-definition map. The algorithm is constructed in the form of a multi-rate Kalman filter that compensates for the delay of the data and updates it asynchronously. The proposed method is easy to apply to systems with different sensor configurations using the loosely coupled method and can provide more accurate localization results.

Keywords: autonomous vehicle, GPS, navigation, prediction, simulation

1 Introduction

Recently, interest in autonomous driving has increased, and many related studies have been conducted. One of the technologies in autonomous driving, vehicle location estimation, is an essential technology for planning or controlling the path of autonomous vehicles. GPS is widely used to measure the position value of moving objects. However, GPS measures position values at low frequencies of about 5 Hz but cannot obtain accurate values due to wrong signals in complex urban environments[1]. The position is estimated mainly in combination with the value of dead reckoning results using in-vehicle sensors or external IMU, which provide values at high intervals, to solve this problem[2]. However, this method has the disadvantage of lowering the reliability of the final location prediction value accordingly when the GPS measurement value is low for a long time. Therefore, in such an urban environment, position estimation results using recognition results using cameras or lidars are combined and utilized[3, 4]. However, the position results measured or calculated using such sensor data are delayed for various reasons. In the case of GPS sensors, delays occur as they pass through the ionosphere and troposphere when receiving signals from extraterrestrial satellites[5]. When position values are obtained by matching them with an HD map using LiDAR or camera data, many point groups or image data are preprocessed and delayed. In this case, the measurement value is updated before the delay occurs, which may act as an error occurrence factor during high-speed driving. Therefore, this paper proposes a method of compensating and combining the delay time of GPS measurements with the lane detection results recognized through the vehicle's front camera using a multi-rate Kalman filter.

2 Test Environments

2.1 VTD Scenario

The test was conducted in a virtual test drive (VTD) simulation environment. The simulation environment was constructed using map data using openCRG and open DRIVE created by simulating actual roads. The scenario consists of a one-way operation from the starting point to the arrival point of the BRT route in Cheongna New Town, Korea. The IMU value, position value, and front camera image provided in the simulation were all acquired asynchronously in the form of ROS topic. Figure 1 shows Chungra city map for simulation.

Figure 1: Chungra City Map in VTD Simulation

2.2 GPS Sensor Model

Since the GPS sensor model was not provided in the VTD, we constructed a sensor model reflecting the characteristics of GPS. As mentioned in the introduction, GPS sensors receive delayed signals because they determine their position through satellite signals outside the Earth. In addition, the tendency of GPS errors is somewhat biased without the Gaussian distribution. First, to reflect the characteristics that tend to be biased, the error value was set to the previous error value plus the random value, not set to the new random value every time.

In addition, the maximum value and the variance value were determined by dividing the size value of the error into the tunnel section, the urban section, and other sections with good reception. The queue was used to implement the delay phenomenon of GPS sensors. As shown in Figure 2, a position value reflecting the previous error push into the queue and a position value before a predetermined delay time from the current time is output as a GPS measurement value. It also outputs down sampled results for the typical output period of GPS.

3 Proposed Method

3.1 Lane Detection

Although several lane detection methods exist[6, 7], we used rule-based methods without deep learning. First, we extracted white, blue, and yellow areas inside the ROI(region of interest) after converting the RGB image into an HSV image. The ROI was set to a section of about 13m to 40m in front of the vehicle due to the limitation of the angle of view of the front camera. The ranges of each of the three colors are changed adaptively according to the average brightness information of the image. Through this, lanes

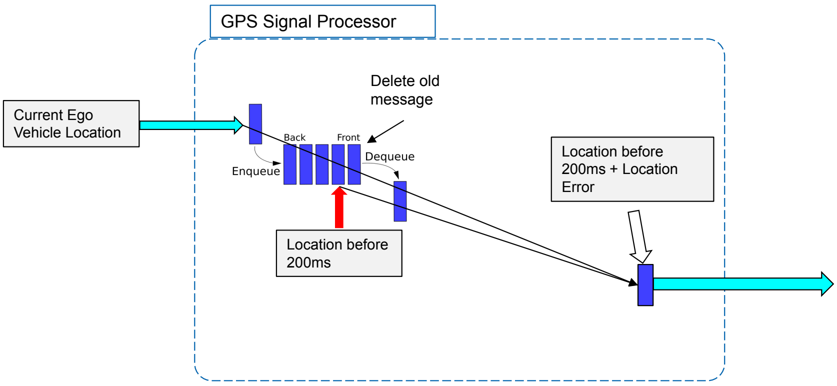

Figure 2: Architecture of GPS Sensor Model

could be strongly recognized even in sections such as inside the tunnel. After closing the previously extracted binary image, find a straight-line component using the Hough transformation. Based on the slope sign, the detected straight lines were divided into a left and right lane candidate groups. The middle straight line between the average value of the divided left-lane candidate group and the average value of the right-lane candidate group was used as the lane recognition result. In this case, when the difference in slope between the detection results of the left and right lanes is significant, it is judged as a false detection and is not used for position estimation.

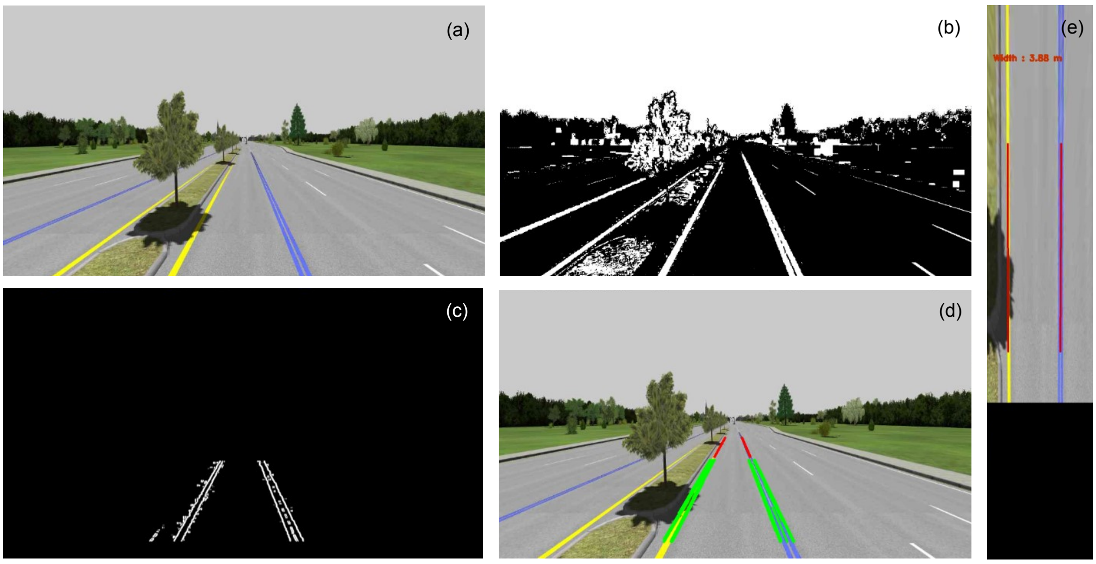

Figure 3: Process of Lane Detection Algorithm (a) Raw Camera image (b) HSV Image based Color Filtering (c) Edge Detection in ROI (d) green : Hough Transform Result, red : Average of Left and Right Lanes (e) Top View of Lane Detection Result

3.1.1 Localization using Lane Detection Result and HD Map

We combined HD map information and lane detection results to obtain position values. The information obtained through lane detection is a lateral offset in the current lane, so the current position value is required to know which lane and road the vehicle is in. Therefore, the lane information being driven is determined based on the estimated position when the camera image was acquired. For this position value, the corrected lateral offset value in the current lane will be used to estimate the position value. However, the vehicle's position changed during the pre-processing process for lane detection and matching with the HD map after the camera image acquisition, so additional compensation is necessary.

The dead reckoning provides accurate values within a short period. We finally updated the filter with the compensated results by the displacement of dead reckoning results over the delayed time.

3.2 GPS Delay Estimation

The filter was constructed to estimate the delay time and update the compensated value under the assumption of a first-order linear delay[8]. In addition to the current vehicle position value, the GPS measurement value is added to the state variable to update its position. Equations (1) and (2) show the state vector and control input of the filter. Furthermore, equations (3) - (8) show the prediction step of the filter.

$$\mathbf{x} = [X, Y, X_{gps}, Y_{gps}, \psi, \tau^{-1}]^T \tag{1}$$

$$\mathbf{u} = [v, \dot{\psi}]^T \tag{2}$$

$$X_{k|k-1} = X_{k-1} + cos(\psi) \times v \times dt \tag{3}$$

$$Y_{k|k-1} = Y_{k-1} + sin(\psi) \times v \times dt \tag{4}$$

$$X_{gps_{k|k-1}} = X_{gps_{k-1}} \times (1 - dt \times \tau^{-1}) + X_{k-1} \times dt \times \tau^{-1} \tag{5}$$

$$Y_{gps_{k|k-1}} = Y_{gps_{k-1}} \times (1 - dt \times \tau^{-1}) + Y_{k-1} \times dt \times \tau^{-1} \tag{6}$$

$$\psi_{k|k-1} = \psi_{k-1} + \dot{\psi} \times dt \tag{7}$$

$$\tau_{k|k-1} = \tau_{k-1} \tag{8}$$

GPS result fail/safe is determined by whether the difference between the current predicted value and the GPS result exceeds a predefined threshold[9]. If the GPS value is judged to be safe, the filter is updated, and if it is not, it is not updated.

3.3 Multi-rate Kalman Filter

The proposed system is based on the extended Kalman filter. In the prediction step of the model, dead reckoning is performed using vehicle speed and sampling time interval as input values. In the update step, correction is performed based on the measurement values of the two sensors, GPS and camera. Since the input period of the inertial sensor used for prediction, GPS, and the camera used for the update are different, a calculation is conducted asynchronously when input from each sensor is received using the multi-rate Kalman filter structure[10]. Such a loosely-coupled system has an advantage in ease of adding or removing other sensors for state estimation. Figure 4 shows a system overview of the proposed localization system.

4 Results

4.1 GPS Delay Estimation

Figure 5 shows the GPS latency prediction results through the filter. During GPS modeling, the actual value of the delay time was set to 200 ms, and the initial delay time value of the filter was set to 400 ms. The result of gradually converging to the actual value could be confirmed. When the average value after converging near the actual value was calculated, the result was 193 ms, which was 7 ms different from the actual value.

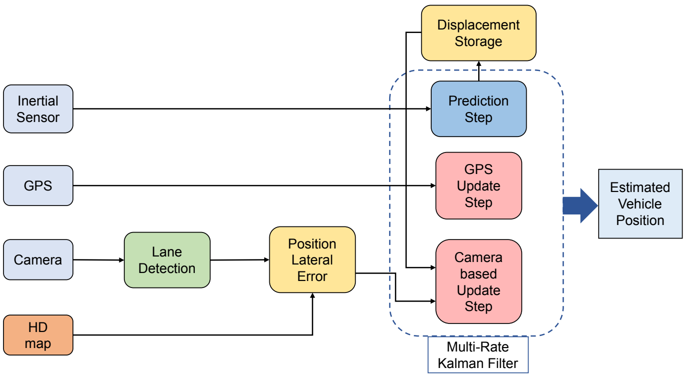

Figure 4: Overall System Architecture

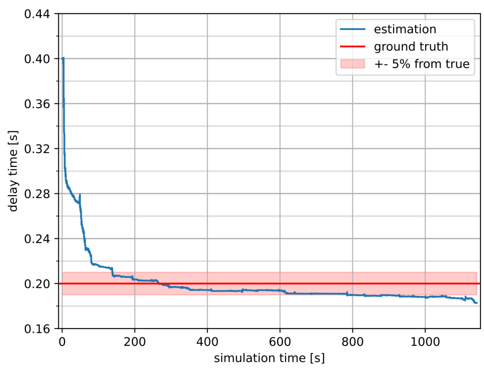

Figure 5: Result of GPS Delay Time Estimation

4.2 Localization

Figure 6 shows the overall positioning result. When looking at the partially enlarged result, the size of the error is smaller than the GPS value. In Figure 6, there are sometimes significant errors that occur due to a processing error as a result of lane recognition.

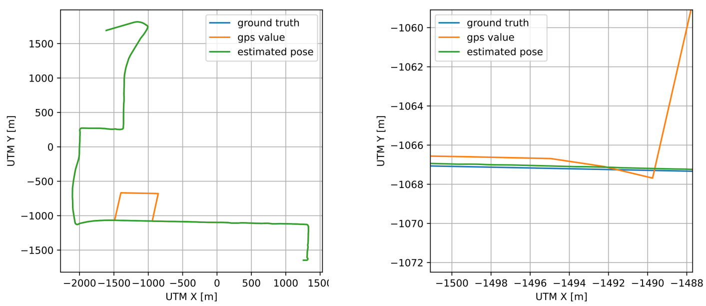

Figure 6: Localization Result

Figure 8 and Table 1 show errors in cases where the compensation algorithm for delay time is applied and where the compensation algorithm is not applied. In Figure 8, the lateral error value was similar in the two cases, but the longitudinal error value showed a slight improvement when the algorithm was applied. Table 1 shows the RMS error in each case. In terms of longitudinal error, the improvement was about 7%, and the overall error was improved by about 5%.

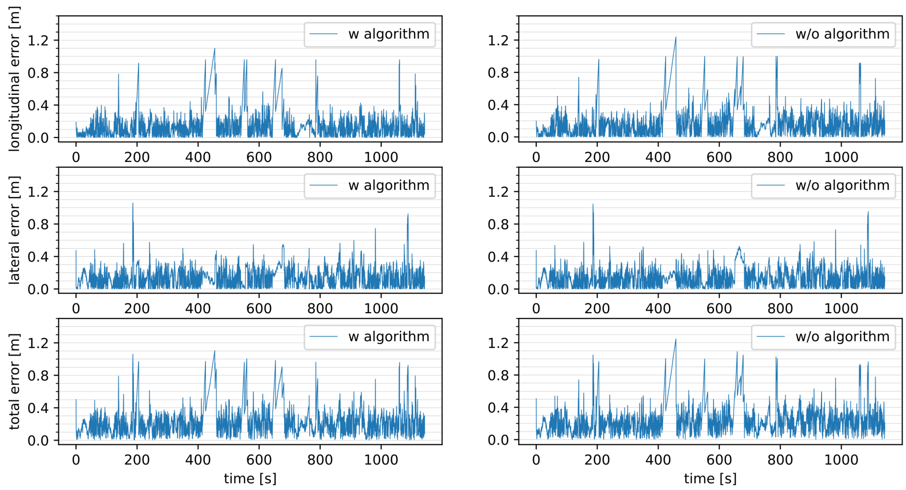

Figure 7: Result of Localization

These results show that our proposed algorithm works well.

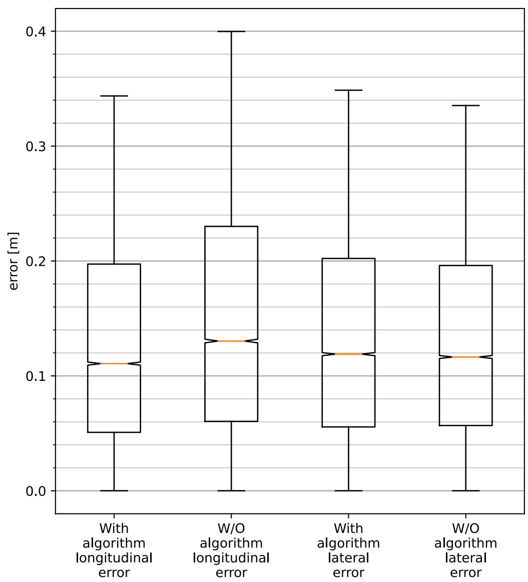

Figure 8: Comparison of Differences according to Applying Proposed Algorithm

Table 1: Longitudinal/Lateral/total RMS Error

	RMSE With Algorithm (cm)	RMSE W/O Algorithm (cm)	Improvement (%)
Longitudinal	25.05	27.13	+7.67
Lateral	18.32	18.31	-0.05
Total	31.03	32.73	+5.19

5 Conclusion

This paper proposed an algorithm that can perform more precise positioning by compensating for delay factors that may occur during sensor fusion. First, we constructed a test environment using VTD and proposed a GPS signal generation method considering the characteristics of GPS. Furthermore, we proposed an asynchronous filter using GPS and front camera images to localize autonomous vehicles. The delay time of GPS was compensated using a model assuming a first-order linear delay, and the data processing delay time of the front camera image was compensated through dead reckoning cumulative displacement. Finally, we verified the performance of the proposed algorithm through simulation experiments. More remarkable performance improvement can be expected if the algorithm is used in a faster driving environment than in this simulation experiment.

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