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Localization using Dual Fail/Safe Filters with Sensor Fusion in Complex Urban Environments

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Summary

It is difficult to obtain reliable data without proper calibration because variations in illumination and surroundings in complex urban environments affect the sensor input. This study proposes a localization algorithm using sensor fusion in complex urban environments, that applies a fail/safe filter to improve the reliability of data obtained from sensors that reduce dependence on the characteristics of the surrounding environments.

This study proposes a sensor fusion localization algorithm in complex urban environments that applies a fail/safe filter to improve the reliability of data obtained from the sensors that are less affected by the characteristics of the surrounding environments. LiDAR reflections provide data that is unaffected by illumination changes, and can be used for sensor fusion by calibrating in-vehicle sensors rather than expensive IMUs. The fail/safe filter compares the curvature of the lane or the distance traveled, and determines the boundary point using the rate of change of the sensor and vehicle model. The boundary points and position data are compared to determine the reliability of the data. The performance of the proposed filter was verified by applying it to a real vehicle in K-City and Suseong Alpha City.

Keywords: autonomous vehicle, Sensor Fusion, HD Map, Localization, Complex Urban Environment

1 Introduction

Recently, interests in sharing and autonomous transportation have increased, and researches on localization in complex urban environments, which is one of the essential technologies, have also attracted much attention. Global navigation satellite systems are commonly used for localization, but the results provide low positioning accuracy due to low frequencies[1,2], making them unreliable in complex urban environments. Although sensor fusion with dead reckoning has been studied, however, dead reckoning has limitations that it is vulnerable to long-term GNSS errors in complex urban environments. Other attempts have been made to improve performance through sensor fusion with different ways of dead reckoning, but there were still limitations[3]. Fusion using cameras and HD maps has also been studied[4], but in complex urban environments, cameras provide inaccurate locations due to unreliable data from variations in illumination.

This study improves the reliability of the sensor data itself by using in-vehicle lidar, which is not affected by the surrounding environment, including changes in illumination. A dual fail/safe filter further improves the reliability of the sensor data, and the output is passed on to the master filter to apply the localization algorithm for complex urban environments.

2 Sensor Calibration

2.1 GPS Latency

The output from GPS passes through a filter algorithm within the sensor, and since data has to then be transmitted, there is a delay from the time the actual data was captured. We used an algorithm to measure the delay through a test, and we store the delay information in the buffer [5].

2.2 Offset of In-vehicle Sensors

If the heading is calculated using the output value of the Yaw rate sensor mounted on the vehicle, the vehicle can be seen to radiate in one direction even though the vehicle is not rotating. This happens when the zero point of the yaw rate sensor has not been set correctly. We solve this problem by determining the offset error value through a test, and then we compensate for the offset every moment.

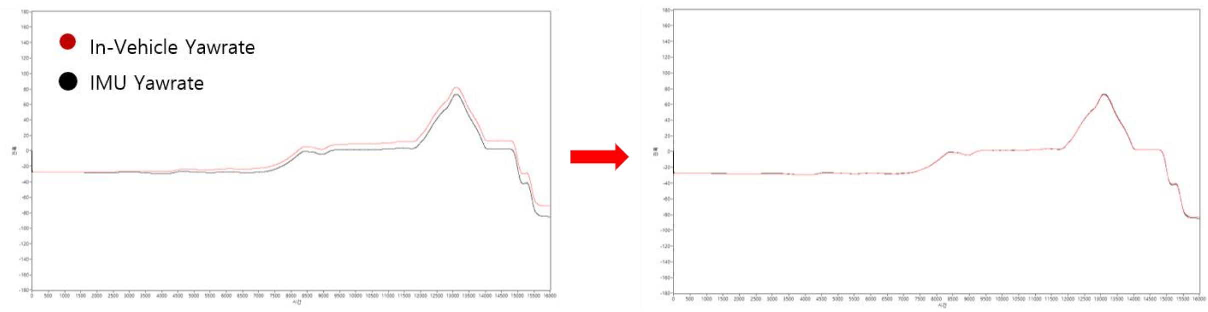

Figure 1: Yaw rate Sensor Error state

2.3 Mounting Position Compensation for LiDAR Sensor

In this study, 16-channel LiDAR is mounted on the bumper of a vehicle and is used for lane recognition. In the figure below, we compare raw data from 64-channel LiDAR and 16-channel LiDAR mounted on the vehicle's roof. The comparison showed no problem with the 64-channel LiDAR. However, 16-channel LiDAR has a relatively large dead zone between the layers.

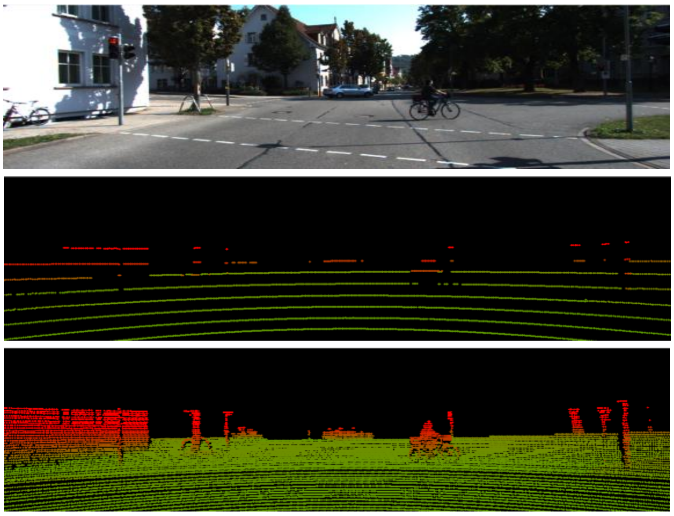

Figure 2: KITTI Datset, Mounting Position (roof) and Channel Count Comparison

3 Fail/Safe Filters using Sensor Fusion

3.1 Fusion Dead Reckoning using In-vehicle Sensors

Choosing the right model can improve the sensing performance. The CTRV and CTRA models provide better performance than a simple CV model in almost all cases, and in high-acceleration situations, the CTRA model outperforms the CTRV model. The motion and position data calculated in this way is mainly used for the fail / safe filter that determines the reliability of the sensor data. [3]

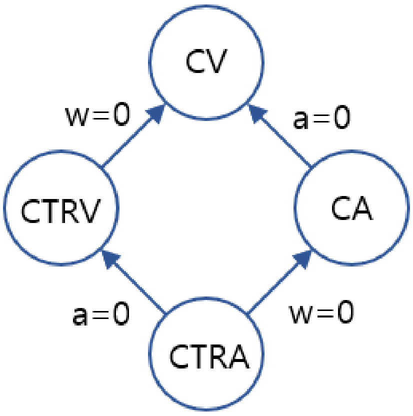

Figure 3: Overview for linear and curvilinear motion models

Equations (1), (2), and (3) are the equations of the vehicle model of the constant velocity model (CV).

$$X_{k+1} = X_k + Tv_k \cos(\psi_k) \tag{1}$$

$$Y_{k+1} = Y_k + Tv_k \sin(\psi_k) \tag{2}$$

$$\psi_{k+1} = \psi_k + Tw_k \tag{3}$$

Equations (4), (5) and (6) are the equations of vehicle model of the constant acceleration model (CA).

$$X_{k+1} = X_k + Tv_k \cos(\psi_k) + \frac{1}{2}T^2 a_k \cos(\psi_k) \tag{4}$$

$$Y_{k+1} = Y_k + Tv_k \sin(\psi_k) + \frac{1}{2}T^2 a_k \sin(\psi_k) \tag{5}$$

$$\psi_{k+1} = \psi_k + Tw_k \tag{6}$$

Equations (7), (8) and (9) are the equations of vehicle model of the constant turn rate and velocity model (CTRV).

$$X_{k+1} = X_k - \frac{v_k}{w_k}\sin(\psi_k) + \frac{v_k}{w_k}\sin(Tw_k + \psi_k) \quad (7)$$

$$Y_{k+1} = Y_k + \frac{v_k}{w_k}\cos(\psi_k) - \frac{v_k}{w_k}\cos(Tw_k + \psi_k) \quad (8)$$

$$\psi_{k+1} = \psi_k + Tw_k \quad (9)$$

Equations (10), (11) and (12) are the Equation of vehicle model of the constant turn rate and acceleration model (CTRA).

$$X_{k+1} = X_k + \frac{v_k}{w_k}[\sin(Tw_k + \psi_k) - \sin(\psi_k)] + \frac{a_k}{w_k^2}[\cos(Tw_k + \psi_k) - \cos(\psi_k) + \mathrm{T}w_k \sin(Tw_k + \psi_k) \quad (10)$$

$$Y_{k+1} = Y_k - \frac{v_k}{w_k}[\cos(Tw_k + \psi_k) - \cos(\psi_k)] + \frac{a_k}{w_k^2}[\sin(Tw_k + \psi_k) - \sin(\psi_k) - \mathrm{T}w_k \cos(Tw_k + \psi_k) \quad (11)$$

$$\psi_{k+1} = \psi_k + Tw_k \quad (12)$$

3.2 Sensor Fusion & Fail/Safe Filter 1 (GPS & In-vehicle Sensors)

The weight factor is used to take into account the importance of the filters by comparing the number of extracted points, including HDOP of NMEA, GPS FIX information of NMEA, and number of connected satellites. The position comparison filter compares the moving distance and, in the case of the position & motion filter, derives the boundary point using the rate of change of the sensor and the vehicle model. The boundary points and position data are compared to determine the reliability of the data.

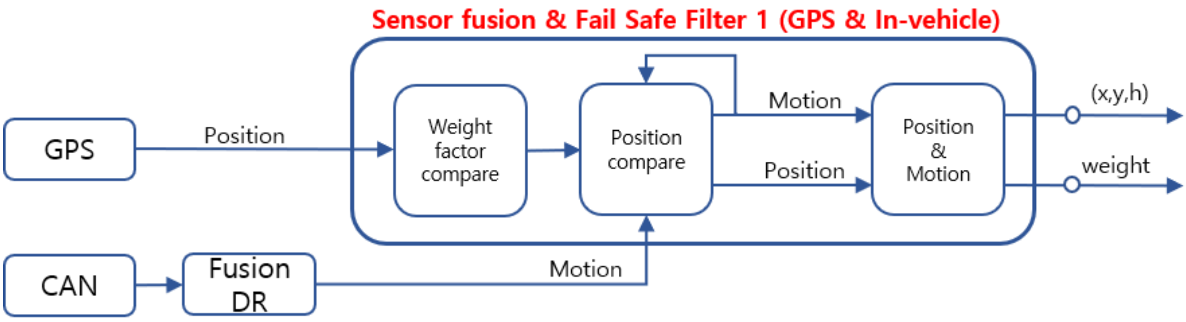

Figure 4: Search scheme for the the sensor fusion & fail/safe filter 1

The position comparison filter determines the reliability of the data by comparing the GPS travel distance with the vehicle model travel distance. However, if the GPS condition is actually in error, as shown below, it can be recognized as normal. Therefore, additional reliability tests should be applied.

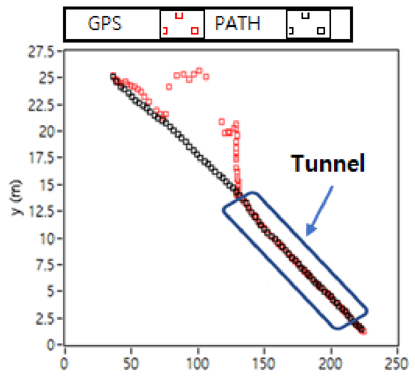

Figure 5: GPS Error state

The position & motion filter determines the fail/safe using a boundary point of the position sensor and motion sensor. The left side of Figure 6 shows the part that derives the two boundary points, and the right side shows the fail/safe judgment based on the position of the position sensor around the two boundary points.

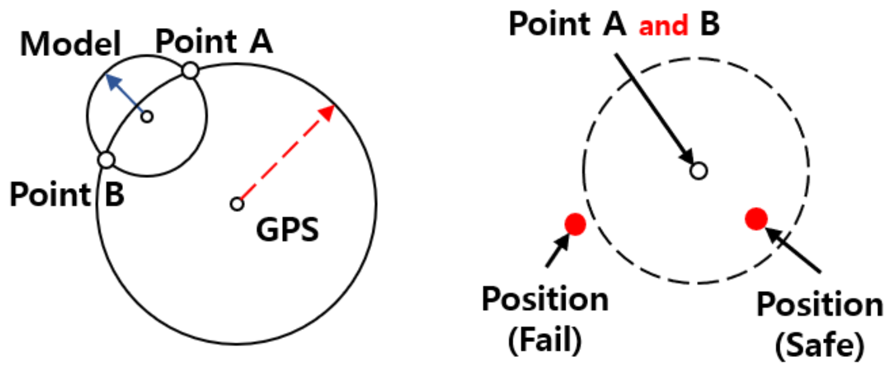

Figure 6: Fail/safe filter using position & motion sensor fusion

3.3 Sensor Fusion & Fail/Safe Filter 2 (LiDAR & In-vehicle Sensors)

A curve matching filter compares the lane data of the hd map to determine its reliability. In the case of the LiDAR & Motion filter, it derives the boundary point using the lane data and the rate of change of the vehicle model. The boundary points and position data are compared to determine the reliability of the data.

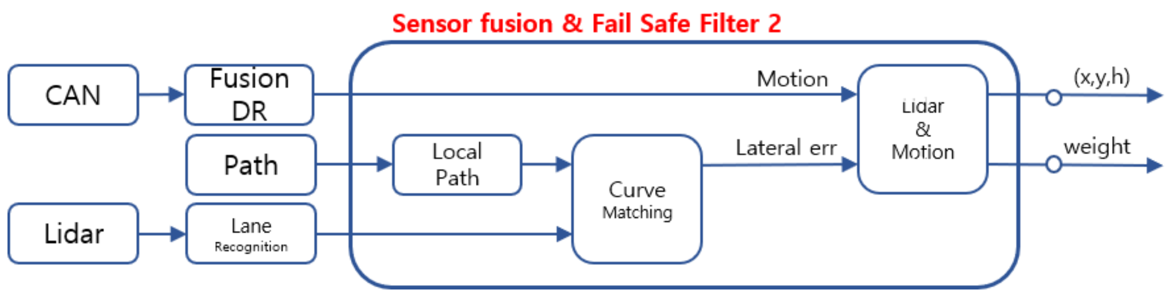

Figure 7: Scheme of searching the sensor fusion & fail/safe filter 2

The curve matching filter compares the results of the lane recognition with lane data on an HD map to determine the reliability. As a result of lane recognition using a camera in a complicated urban environment, there was a situation where the camera could not be trusted due to the change in illuminance. To solve this problem, we implemented lane recognition with LiDAR, which is not affected by the changes in illuminance. The figure below shows a situation where the camera did not recognize a lane when the algorithm was tested in urban environment. [6~9]

Figure 8: Camera Lane Recognition Error State

LiDAR & Motion filters use lane data and the rate of change of the vehicle model to derive boundary points A and B. By comparing the weights, one boundary point is selected and compared with the positional data to determine the reliability of the data. The figure on the left shows the curve matching filter, and the figures in the middle and right show the LiDAR & motion filter.

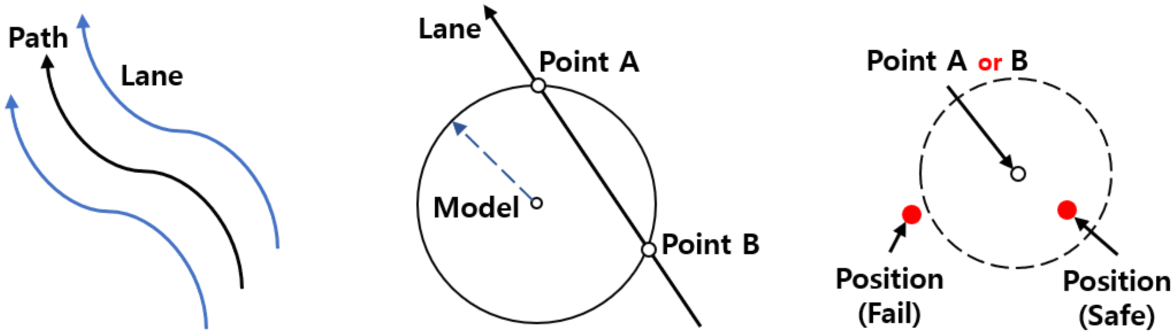

Figure 9: Curve maching fail/safe filter and lidar & motion fail/safe filter

4 Experimental Results applying the Proposed Algorithm

4.1 Double Fail/Safe Filters using Sensor Fusion (GPS, LiDAR & In-vehicle Senors)

The fail/safe filter consists of GPS, in-vehicle filter and Lidar and In-vehicle filter. The role determines the reliability of the sensor data and delivers it to the master filter. Localization algorithms were tested with various master filters reflecting the fail/safe filter in a complex urban environment. The test consisted of three types: non filter, EKF, and particle filter, and localized with reliable data, which showed nearly accurate localization results.

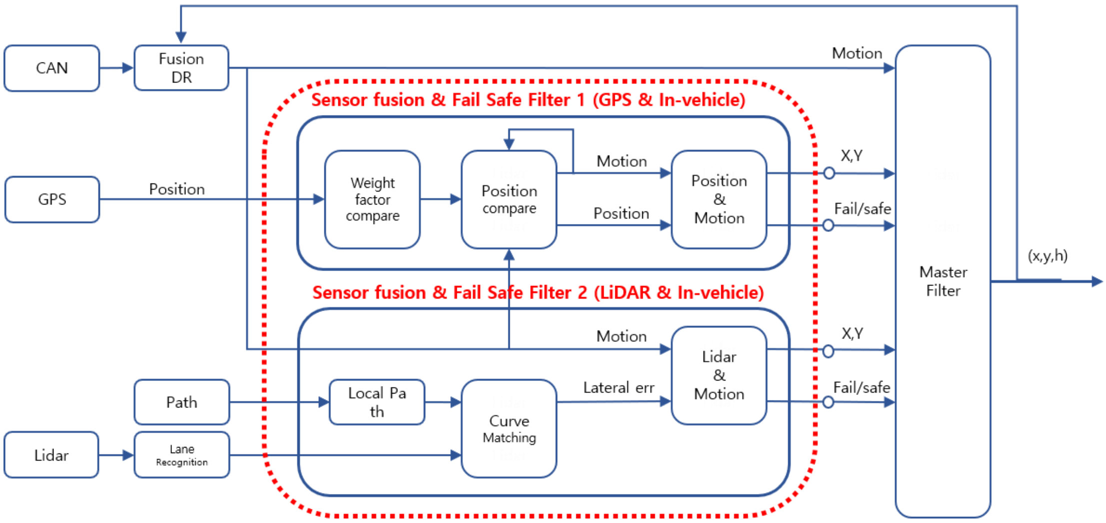

Figure 10: Scheme of searching the localization based on sensor fusion in urban areas

4.2 Test Results in Complex Urban Environments

The algorithm was tested in a complex urban environment. In fact, when passing through a tunnel, there was a situation where GPS and camera recognition were impossible. The in-vehicle sensor, which is not affected by the surrounding environment, and the LiDAR sensor, which is not influenced by the changes in illumination, were transferred to the master filter, which resulted in reliable localization. In the figure below, the left side shows the case where the camera is not recognized and the GPS data is omitted. We can see that we implement a relatively accurate localization using the proposed algorithm. The figure on the right shows the sensor placement of the test vehicle, and tests were conducted in tunnels and urban environments over 200m.

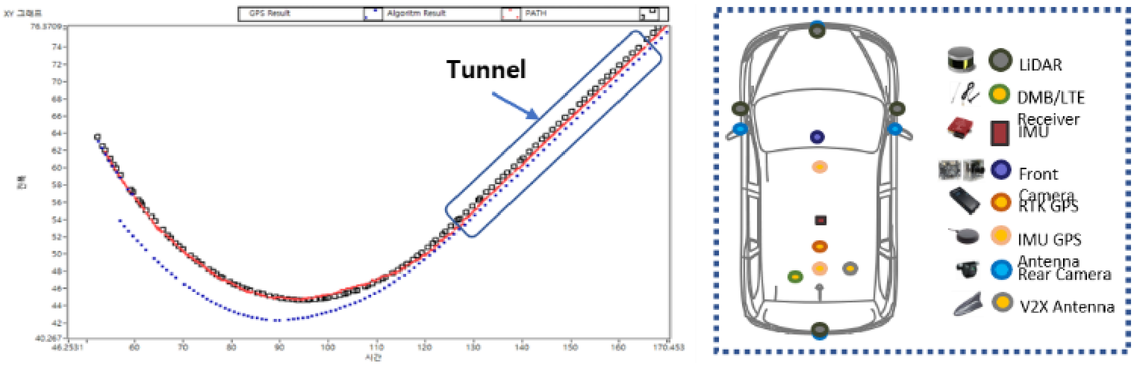

Figure 11: Algorithm Results (K-city) & Experiment Vehicle (i30)

5 Conclusion

In this study, a sensor fusion method is proposed that is less affected by changes in illuminance and the surrounding environment. Through this, it is possible to provide stable data even in a complex urban environment. In addition, a more stable sensor value was derived using a fail / safe filter, and finally, stable localization was implemented. To overcome the limitations of the fail / safe method using the rate of change of the sensor, a dual fail / safe structure was applied. The proposed algorithms (K-City and Suseong Alpha City) were tested on real roads to obtain reliable failure / safety algorithms and localization results.

6 Future Work

In future work, we will study robust location estimation algorithms that further reduce the dependence on GPS by adding sensor-based data. A robust matching algorithm using HD MAP will also be developed. It will also reinforce the conditions for fault/safety judgment and apply the correct vehicle model to the master filter. To obtain an accurate vehicle model, an expensive INS equipment will be used to derive a 2D map with model parameters, and tests will be conducted on actual roads to verify the algorithm. In addition, we will study sensor errors that may occur depending on the weather and apply them to location estimation.

Acknowledgments

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