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Paper:

Localization System for Vehicle Navigation Based on GNSS/IMU Using Time-Series Optimization with Road Gradient Constrain

Aoki Takanose*, **Kaito Kondo****, **Yuta Hoda****, **Junichi Meguro****, **and Kazuya Takeda***

*Graduate School of Informatics, Nagoya University
Furo-cho, Chikusa-ku, Nagoya, Aichi 464-8603, Japan
E-mail: takanose.aoki@g.sp.m.is.nagoya-u.ac.jp
**Department of Mechatronics Engineering, Graduate School of Science and Technology, Meijo University
1-501 Shiogamaguchi, Tempaku-ku, Nagoya, Aichi 468-8502, Japan
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In this paper, we propose a GNSS/IMU localization system for mobile robots when wheel speed sensors cannot be attached. Highly accurate location information is required for autonomous navigation of mobile robots. A typical method of acquiring location information is to use a Kalman filter for position estimation. The Kalman filter is a maximum-likelihood estimation method that assumes normally distributed noise. However, non-normally distributed GNSS multipath noise that frequently occurs in urban environments causes the Kalman filter to break down, and degrades the estimation performance. Other GNSS/IMU localization methods capable of lane-level estimation in urban environments use wheel speed sensors, which are unsuitable for the present situation. In this study, we aim to improve the performance of lane-level localization by adding a vehicle speed estimation function to adapt the method to those requiring wheel speed sensors. The proposed method optimizes time-series data to accurately compensate for accelerometer bias errors and reduce GNSS multipath noise. The evaluation confirmed the effectiveness of the proposed method, with improved velocity and position estimation performance compared with the Kalman filter method.

Keywords: autonomous mobile robot, localization, GNSS/IMU, urban environment, low cost sensors

1. Introduction

In recent years, the field of autonomous navigation of mobile robots, including vehicles, has gained great attention [1–3]. Various studies are being conducted to realize the goals of reducing traffic accidents [4], improving traffic flow [5], and reducing the burden on drivers [6]. Autonomous driving technology is composed of various technological elements [7–9]. In the structure [9], the control object receives the amount of operation comprehensively determined by perception, planning, and decision, based on the collected sensor information and maps. In this study, we targeted the location estimation technology in the perception component of these elements [7, 9]. Providing highly accurate location information is essential because object recognition, route planning, and vehicle control are often performed based on this information. Considering an automobile as an example, reference [10] states that a position accuracy of approximately 0.3 m is required. When using cameras, light detection and ranging (LiDAR), etc., it is assumed to have an accuracy of about 1.5 m, which is at the lane level.

To achieve the required position estimation performance, methods using cameras and LiDAR have been proposed [11–15]. Map information, such as street view in method [11] and 3D point clouds in method [12], must be prepared in advance. This map information changes over time and is expensive to maintain. The development of simultaneous localization and mapping (SLAM) technology has made it feasible to create low-cost, high-precision 3D point clouds, which used to be very expensive earlier. However, 3D LiDAR is still an expensive sensor, costing more than 5,000 dollars. Therefore this remains a challenge from the perspective of wide adoption.

Considering these cost issues, this study examines a location estimation method using global navigation satellite system (GNSS) and inertial measurement unit (IMU) fusion. GNSS does not require any prior information such as maps, and location information can be easily obtained. However, multipath occurs when satellite signals are reflected and/or diffracted by obstacles such as high-rise buildings in urban environments. Multipath causes a significant degradation in positioning performance. Although there is a method for adopting a highly accurate positioning system (such as POSLV [a]) for surveying applications even in urban environments, it is very expensive because of its surveying and mapping application.

To solve this problem, a position estimation method using low-cost sensors has been proposed [16]. The method [16] achieved lane-level accuracy in urban environments and was confirmed to be equivalent in performance to survey systems. However, these methods use wheel speed sensors and often require vehicle modifications. Consequently, the overall cost is high. Furthermore, if a wheel speed sensor cannot be installed due to the size or structural limitations of the vehicle, this method cannot be applied directly.

In this study, we propose a GNSS/IMU-only position estimation method that does not require wheel speed sensors for existing vehicles and robots that cannot be equipped with wheel speed sensors. Specifically, we target lane-level equivalent position estimation by adding a new velocity estimation method to that of [16], which requires a wheel speed sensor.

Several existing GNSS/IMU applications focus only on positional information and neglect velocity estimation. Because this research assumes vehicle navigation, velocity estimation performance is also important. Therefore, the proposed method focuses on improving velocity estimation performance and considers an algorithm for lane-level position estimation.

The proposed method estimates velocity by fusing the accelerometer included in the IMU and GNSS Doppler. The cumulative error is a particularly serious problem in velocity estimation using accelerometers. Conventional methods often probabilistically consider this error as bias noise. In contrast, the proposed method accurately estimates the amount of accelerometer error by considering vehicle motion. Furthermore, by utilizing GNSS Doppler, we aim to increase the velocity accuracy. To ensure that we can fully demonstrate these concepts, the velocity estimation of the proposed method is designed with the following features:

- Dynamic correction of the acceleration error using road gradients and vehicle motion constraints.
- Cancellation of the cumulative error of acceleration integration by GNSS Doppler with zero-error mean.
- Optimization of time series data for the above-mentioned purposes.

The main feature of the proposed method is that it is not a sequential optimization, but an optimization with a long data set. This is very useful for removing GNSS multipath and minimizing the cumulative error owing to acceleration integration. The proposed method is expected to be applicable to small robots and robots without wheels, because it employs only a GNSS/IMU sensor unit. In this study, we compare the features of the proposed method with those of related studies and verified the effectiveness of the proposed method through evaluation tests.

2. Related Research

A position estimation method that adopts the Kalman filter was proposed as a typical method for combining GNSS and IMU [17, 18]. The Kalman filter is a type of sequential Bayesian estimation method that is derived when all the noise in the state-space model is assumed to be normally distributed [19]. When the noise is normally distributed, it is confirmed to be an effective state estimation method. Therefore, using the Kalman filter with the GNSS and IMU as observations improves the performance of the GNSS/IMU as a combined navigation arithmetic unit.

However, it is known that GNSS multipath noise in urban environments is non-normally distributed and causes outlier errors. Noise such as this outlier error can degrade the estimation performance of the Kalman filter [20]. To counteract outlier errors, methods such as weighting observations [21] and thresholding using the Mahalanobis distance [22] have been used. However, multipath GNSS outliers are not expected to benefit from these outlier removal functions because the exact error distribution is unknown.

In addition, when dealing with low-cost IMUs, IMU bias must be accurately corrected. Some methods include this bias in the state value and estimate it by using a Kalman filter. The bias of low-cost IMUs is highly variable and difficult to accurately model. Hence, Kalman filters are sometimes designed assuming a small bias variation. In such cases, an accurate bias estimation is difficult when the bias variation is large.

A position estimation method that employs averaging by the least squares method to integrate the GNSS and IMU has also been proposed [16]. The method in [16] is superior in accurately estimating vehicle motion using GNSS Doppler. The cumulative errors of the IMU and wheel speed sensors were minimized by averaging the corrections that accounted for the vehicle motion. Therefore, the trajectory generation is highly accurate even for long integrated vehicle trajectories. Vehicle trajectories are also effective in removing outliers due to the GNSS multipath. When using the Kalman filter, it is necessary to determine whether the GNSS positioning solution is an outlier. On the other hand, the method [16] can comprehensively determine the GNSS positioning solution from the past trajectory. Therefore, it overcomes the issues raised by the Kalman filter method and enables lane-level position estimation even in urban environments. However, this method [16] assumes that wheel speed sensors are installed and that vehicle speed information is available. In this study, the method [16] could not be adapted to applications where speed information was not available from the wheel speed.

3. Proposal Method: Velocity Estimator

3.1. Overview of Velocity Estimation

Figure 1 shows a block diagram of the proposed method. In this study, our goal is to improve the lane-level position estimation performance of the GNSS/IMU position estimation method, even in urban environments. The method [16] can estimate lane-level positions in urban areas; however, it assumes that the wheel speed is available. The proposed method aims at lane-level position estimation using other methods to compensate for the speed information required by the method [16].

Various methods are available for estimating speed.

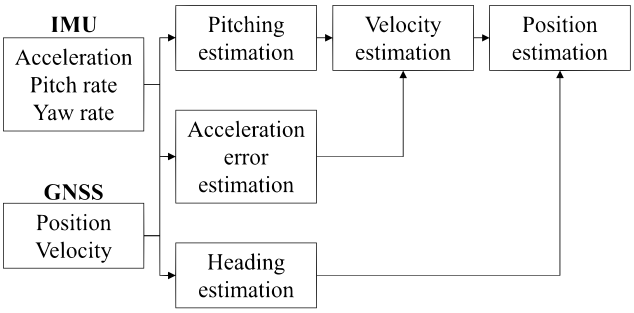

Fig. 1. Block diagram of the proposed method.

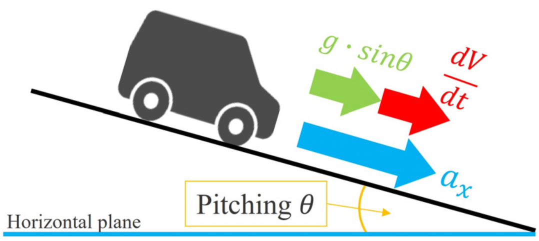

Fig. 2. Components of the acceleration integration model.

The most common method is to integrate the accelerations measured using an accelerometer [23]. Velocity estimation via acceleration integration is highly continuous and smooth. However, owing to sensor errors in the accelerometer, the accumulated error increased over a long period. Another method uses the GNSS Doppler velocity [24]. GNSS Doppler has a very high accuracy with a velocity error of 0.1 m/s in an open sky environment. Furthermore, the error trend of GNSS Doppler is known to be zero because it does not include bias. However, in urban environments, the GNSS is subject to multipaths, resulting in very large errors. The integration of these methods has also been proposed. However, as discussed in Section 2, it is necessary to accurately account for the accelerometer bias noise and GNSS outliers subject to multipaths.

In this paper, we propose a velocity estimation method based on the fusion of acceleration integration and GNSS Doppler data over a long period. This proposed method aims to overcome issues related to each sensor by using data for a long time. This is because they can be solved by using statistical method. Therefore, a key feature of the proposed method is that there is no need to deal with instantaneous outlier removal and bias fluctuations, as with the Kalman filter.

The proposed method minimizes the cumulative error of the acceleration integration before fusing the acceleration integration and GNSS Doppler. The velocity estimation model based on the acceleration integration used in the proposed method is shown in Eq. (1). **Fig. 2** presents a summary of the model.

$$V_{imu}(t) = V_{imu,0} + \int a_x(t) + \delta a_x(t) - g\sin\theta(t)\, dt, \quad (1)$$

where, V_{imu} is estimated velocity by acceleration integration, $V_{imu,0}$ is initial velocity by acceleration integration, a_x is acceleration, δa_x is acceleration error, g is gravity acceleration, and θ is pitch angle. Eq. (1) is a model that integrates acceleration based on the equilibrium relationship of forces applied to the vehicle in the situation shown in **Fig. 2**.

In this acceleration integration model, the acceleration error δa_x dominates the cumulative error. Therefore, the acceleration error must be accurately estimated. To improve the accuracy of the acceleration error estimation, the proposed method uses a real-time kinematic (RTK)-GNSS FIX solution. The FIX solution of the RTK-GNSS provides centimeter accuracy in positioning results in a favorable environment. This highly accurate FIX solution for acceleration error estimation is expected to improve accuracy. Finally, the position was estimated using the dead reckoning model with the estimated velocity and RTK-GNSS.

3.2. Pitch Angle Estimation Using Road Gradient

First, the proposed method estimates the pitch angle, which is then used to estimate the acceleration error. The proposed method calculates the pitch angle using the road gradient obtained using the RTK-GNSS FIX solution. The pitch angle can be estimated by extending the heading estimation method [16]. However, the GNSS Doppler used for estimation is less accurate in the height direction than in the plane direction, owing to the geometric constraints of satellite placement. Therefore, the pitch angle accuracy calculated using the height direction of the GNSS Doppler is expected to be low. To solve this problem, the proposed method estimates the pitch angle using the road gradient calculated from the centimeter-accurate FIX solution.

In the pitch angle estimation of the proposed method, the road gradient and the pitch rate of IMU were fused with reference to the method [16]. **Fig. 3** shows the relationship between the FIX solution and the road gradient. As shown in **Fig. 3**, the road gradient can be calculated from the height and horizontal variations of the FIX solution. In this study, the road gradient calculated using this method and the pitch angle of the vehicle were considered as equivalent. In sections in which the road gradient could not be obtained from the FIX solution, it was interpolated using the pitch rate.

Similar to GNSS Doppler, the RTK-GNSS FIX solution is subject to multipath in urban environments. In most cases, the FIX solution is not the output owing to a test [25] in the RTK-GNSS algorithm. However, in practice, there have been cases where the FIX solution is output as a “missed FIX” [26]. The proposed method determines whether a FIX is a “missed FIX” by comparing it with the result of the pitch rate integration. If it is judged as a “missed FIX,” the data are removed and fused for pitch angle estimation.

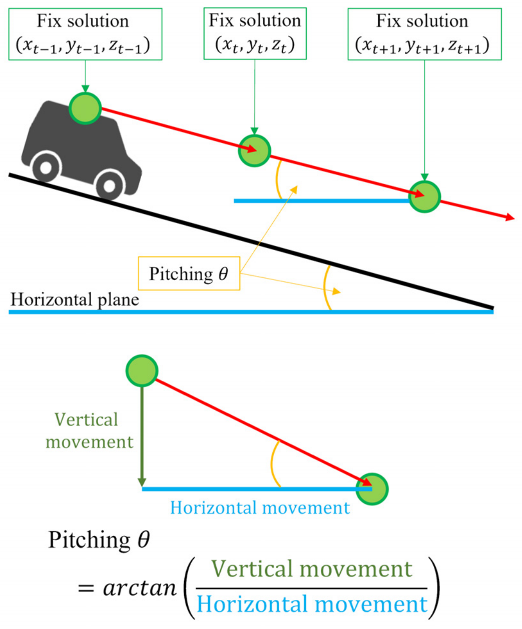

Fig. 3. Pitch angle calculation using road gradient.

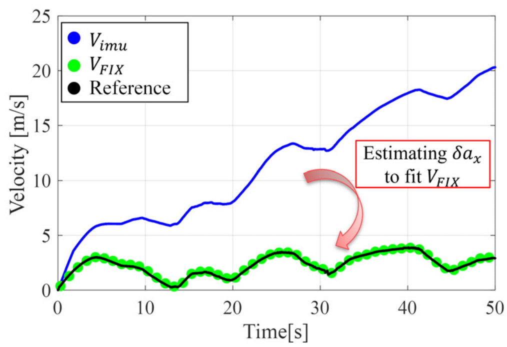

Fig. 4. The cumulative error of acceleration integration.

3.3. Acceleration Error Estimation

This section describes the method for estimating the acceleration error to minimize the cumulative error in acceleration integration. This is an important step in the proposed method for improving velocity estimation accuracy. **Fig. 4** shows how acceleration errors affect the velocity estimation. From **Fig. 4**, it can be observed that the difference from the reference velocity value increases with time in the acceleration integration, which does not consider the acceleration error. The amount of movement of the FIX solution was then determined. The amount of movement of the FIX solution per unit time corresponded to the velocity. This is known as the velocity V_{FIX} of the FIX solution. We can confirm that the velocity V_{FIX} calculated from the FIX solution is highly accurate compared to the reference.

The proposed method estimates the acceleration error by using the velocity of the FIX solution as a constraint. Ideally, the acceleration integral should equal the velocity of the FIX solution. Therefore, the acceleration error was adjusted such that the acceleration integral could be fitted to the velocity of the FIX solution. To estimate the acceleration error, the residual between the acceleration integral and velocity of the FIX solution is minimized. Minimization of the residuals was optimized using the least squares method. The optimization model for the acceleration error estimation is given by Eq. (2).

$$\overline{\delta a_x}(t) = \arg\min_{\delta a_x} \sum \{V_{imu}(t) - V_{FIX}(t)\}^2. \quad \quad (2)$$

For the missed FIX solution, the result determined during pitch angle estimation was used. This method is expected to produce acceleration accumulation results equivalent to the velocity of a highly accurate FIX solution.

This method uses the FIX solution velocity to estimate acceleration error. The same estimation is possible when GNSS Doppler velocity is used. The FIX solution velocity has a lower utilization rate, but outliers occur less frequently, as compared to GNSS Doppler velocity. This is because the tests were performed using the RTK-GNSS algorithm [25]. As accuracy was essential for acceleration error estimation, the velocity of the FIX solution is used in the proposed method. GNSS Doppler is used for the final velocity estimation because its utilization is more important. The use of different velocity information was also intended to avoid the risk of falling into a local optimum.

3.4. Fused Acceleration Integration and GNSS Doppler

By using the pitch angle and acceleration error estimated in the previous sections, it is possible to estimate the velocity using Eq. (1). However, it is difficult to completely cancel the cumulative error because the estimated values of the pitch angle and acceleration errors contain residual errors. It is dangerous to use velocity estimates prone to cumulative errors for position estimation, navigation, and other purposes. Therefore, the proposed method reduces the remaining cumulative acceleration error by fusing it with GNSS Doppler. Because GNSS Doppler has a zero-error mean, it is expected to be effective in canceling the accumulated acceleration error.

The proposed method fuses GNSS Doppler and acceleration integration in the same way as in the pitch angle estimation. The least-squares method was used for integration to estimate the plausible velocity. **Fig. 5** shows a schematic of the fusion of the proposed method, and Eq. (3) shows the velocity optimization model.

$$V_{est}(t) = \arg\min_{V_{imu,0}} \sum \{V_{imu}(t) - V_{doppler}(t)\}^2, \quad \quad (3)$$

where, V_{est} is the estimated velocity and $V_{doppler}$ is the velocity of the GNSS Doppler. As shown in **Fig. 5** and Eq. (3), the proposed method optimizes the initial value of the acceleration integration such that the residuals are minimized. This optimization is a parallel shift in acceleration integration, as shown in **Fig. 5**. Based on the error trend of GNSS Doppler, the proposed method is expected to be effective in further reducing the accumulated error in acceleration integration.

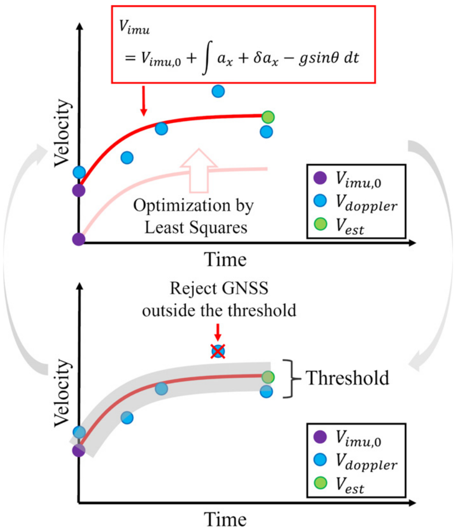

Fig. 5. Velocity estimation of the proposed method: fusion of GNSS Doppler and acceleration integration.

However, GNSS Doppler is subject to multipath in urban environments, which results in outlier errors. Such outliers cause large estimation errors in the least-squares integration. In the proposed method, the GNSS data are considered as multipath data if the residual difference between the acceleration integration and GNSS Doppler is large. Since the multipath-affected GNSS data are generated as an outlier, this GNSS data are rejected and reintegrated. The GNSS data were discarded in the order of the residual difference. Finally, when the residual difference with acceleration integration was within a threshold, the outlier was considered to have been eliminated and the velocity estimate was obtained. By adopting this optimization method, both the cumulative error problem of the acceleration integration and the GNSS multipath problem can be solved in the proposed method.

4. Localization: Dead Reckoning Method

Various methods have been proposed for position estimation, including the Kalman filter and method [16]. Because the proposed method aims to improve the performance of velocity estimation, in this study, the position was estimated by dead reckoning using the RTK-GNSS FIX solution as the initial value. In the section where the RTK-GNSS FIX solution was not available, the position was estimated by inertial navigation using only the GNSS Doppler / IMU. Eqs. (4) and (5) present the dead reckoning model.

$$P_{east}(t) = P_{FIX_{east}}(t) + \int V_{est}(t)\cos\psi(t)\,dt, \quad \ldots (4)$$

$$P_{north}(t) = P_{FIX_{north}}(t) + \int V_{est}(t)\sin\psi(t)\,dt, \quad \ldots (5)$$

where, P_{east} and P_{north} are the estimated positions, P_{FIX} is the FIX solution, and ψ is heading angle. The heading angle ψ is estimated by the method [16].

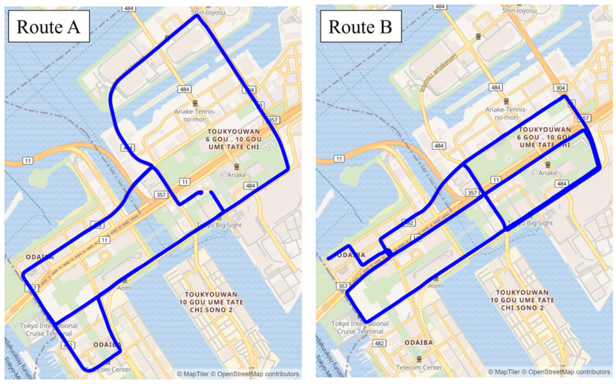

Fig. 6. Driving route for evaluation test.

5. Evaluation Tests

5.1. Summary of Evaluation Tests

Here, we outline the evaluation tests. The evaluation test used OpenDataset [b] published by Meijo University. This dataset was obtained in a real-world environment using the equipment installed in a vehicle. The test environment was Odaiba, Tokyo, which is an urban environment in which multipath occurs frequently. **Fig. 6** shows the evaluation route. The equipment used in the proposed method was an Ublox F9P GNSS receiver and an Analog Devices ADIS16475-2 IMU. Both the sensors are inexpensive. For the true results, we used the post-processing results of POSLV220, which is capable of highly accurate position estimation, even in urban areas. To evaluate the proposed method, we compared and verified the estimation performance and measured the processing time. In the estimation performance evaluation, the estimated values of velocity and position were compared with those of the conventional method. A general Kalman filter was used as the representative conventional method. In the evaluation of the position estimation, the performance limit of the case using the velocity reference was also included in the verification items.

5.2. Overview of Kalman Filter Design

This section describes the design strategy for the Kalman filter used in the comparative tests. State x and observation y of the Kalman filter are designed as follows:

$$x(t) = [P_{east}, P_{north}, V, a_x, \delta a_x, \psi, \theta, \dot{\psi}, \dot{\theta}, \delta\dot{\psi}, \delta\dot{\theta}]^T, \quad (6)$$

$$y(t) = [P_{FIX_{east}}, P_{FIX_{north}}, V_{doppler}, \dot{\psi}, \dot{\theta}, a_x]^T, \quad \ldots (7)$$

where P_{east}, P_{north} are positions, V is velocity, a_x is acceleration, δa_x is acceleration bias error, ψ and θ are attitude angle representing heading and pitch angle, $\dot{\psi}$ and $\dot{\theta}$ are angular velocity representing yaw rate and pitch rate, $\delta\dot{\psi}$ and $\delta\dot{\theta}$ are the bias errors for each angular velocity, P_{FIX} is FIX solution of RTK-GNSS, and $V_{doppler}$ is GNSS doppler velocity. The noise parameters of the Kalman filter were set as shown in **Tables 1** and **2** with reference to [27, 28] and [c].

Table 1. State initial and process noise.

State	Initial noise σ_0	Process noise w
Position	1 m	0.1 m
Velocity	1 m/s	1 m/s
Attitude	3°	0.1°
Angular velocity	0.5°/s	0.5°/s
Gyro bias	0.1°/s	0.01°/s
Acceleration	0.01 m/s^2	0.03 m/s^2
Acceleration bias	0.1 m/s^2	0.01 m/s^2

Table 2. Observation noise.

Observation	Observation noise v
RTK-FIX position	0.3 m
GNSS Doppler velocity	0.2 m/s
Gyro	0.5°/s
Acceleration	0.03 m/s^2

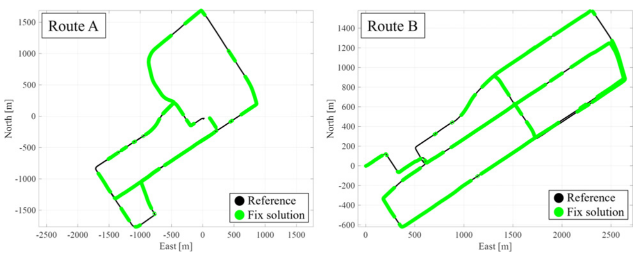

Fig. 7. Acquisition status of FIX solution for RTK-GNSS.

The noise parameter of the Kalman filter has a significant impact on state estimation performance. For example, for velocity, the performance of the acceleration integration model becomes dominant when the process noise is reduced. In contrast, the performance of GNSS Doppler becomes dominant when the observation noise is reduced. In this case, the parameters are designed to achieve the highest performance in a statistical evaluation test. Therefore, the performance of GNSS Doppler was judged to be better than that of the acceleration integration model, and the observation noise was set.

5.3. RTK-GNSS Positioning Results

In the test environment, the positioning results of the RTK-GNSS were first confirmed. **Fig. 7** shows the distribution of the FIX solutions obtained by the RTK-GNSS on the test route. **Table 3** lists the performance of the FIX solutions.

In this evaluation test, the performance of the FIX solution was confirmed to have an mean error of approximately 0.1 m. In **Fig. 7**, there are a few FIX solutions in environments with few visible satellites, such as those under elevated railway tracks. The maximum sections where no FIX solution was obtained were 684.5 m and 532.1 m at each route.

Table 3. FIX solution evaluation results.

	Available rate [%]	Error mean [m]	Error standard deviation [m]
Route A	55.5	0.07	0.29
Route B	75.1	0.13	0.35

5.4. Evaluation Result: Velocity Performance

In this section, we confirm the effectiveness of the velocity estimation using the proposed method. **Fig. 8** shows the cumulative distribution function of the velocity estimation error on the horizontal axis. **Fig. 8** shows that the proposed method has a statistically smaller error than the Kalman filter method. If the vehicle runs 100 m in 10 seconds without a FIX solution, the velocity error must be at least within 0.1 m/s to keep the position error within 1 m. Focusing on a velocity error of 0.1 m/s, we can show that route A and route B improve performance by 16.1% and 8.4%, respectively.

Figures 9 and **10** shows the velocity estimation results for each route. Each result shows that the estimation for the Kalman filter is scattered. This is due to the fact that the observation noise of the Kalman filter is smaller for GNSS Doppler than for acceleration. Consequently, it is considered to be affected by the variation error of GNSS Doppler. On the other hand, reducing the process noise in the acceleration accumulation model produces smooth results with high continuity. In this case, the effect of cumulative errors owing to acceleration errors dominates, and the estimation performance is significantly degraded. For example, in the case where there is no GNSS observation, as shown in the area B of **Fig. 10**, smooth estimation is obtained, but the performance is significantly degraded. The design of the Kalman filter used in this study suppresses the effect of acceleration errors and improves the overall estimation performance by reducing the GNSS Doppler observation noise.

However, the multipath noise of the GNSS causes large outliers in Kalman filter estimates. Methods that reduce the effect of outliers [21, 22] are not expected to significantly improve performance. These methods are characterized by the removal of outliers whose errors follow a normal distribution from a highly accurate prediction model. However, in this test environment, the accuracy of the prediction model based on acceleration summation was low, and the GNSS multipath noise was confirmed to be a non-normally distributed error. Therefore, the contribution to the performance improvement is considered small because accurate outlier removal is not achieved.

Compared to the results of the Kalman filter, the proposed method produced smooth results with a suppressed variation in the estimated values. This is because the effect of cumulative errors owing to acceleration errors is suppressed to the maximum extent possible, resulting in

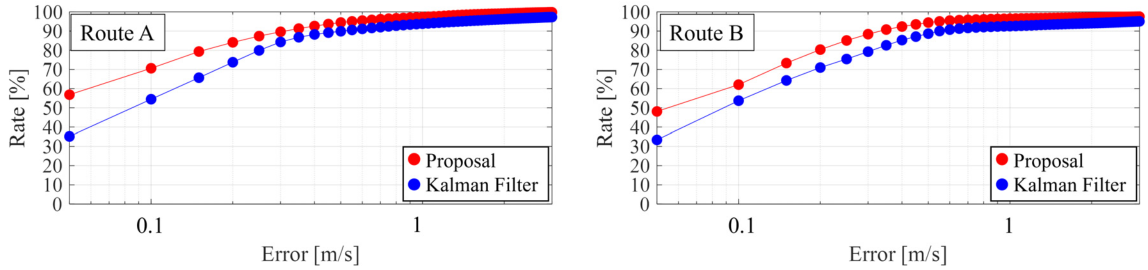

Fig. 8. Evaluation results of cumulative distribution by velocity performance.

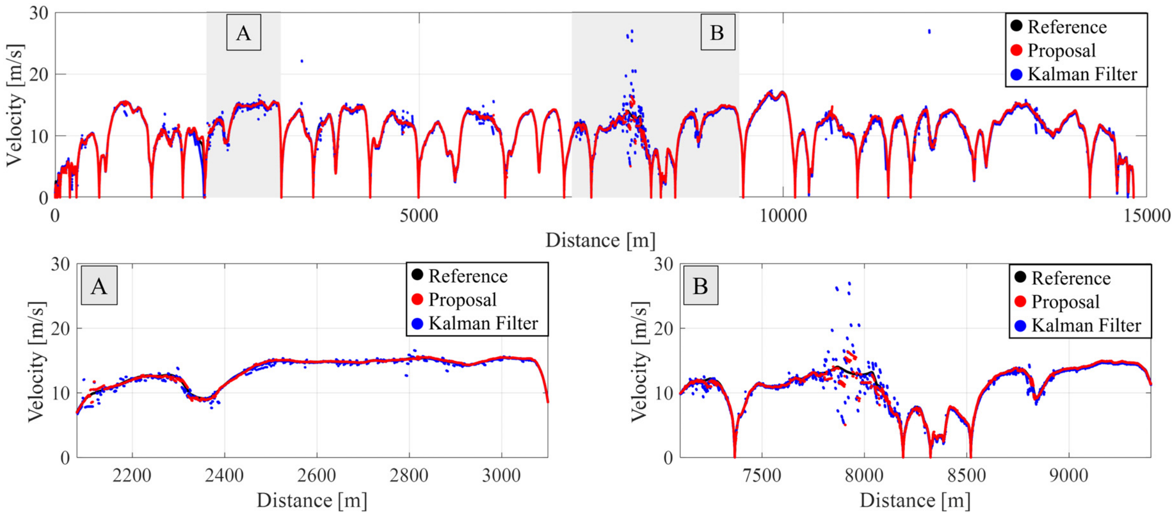

Fig. 9. Velocity estimation results for each method on route A.

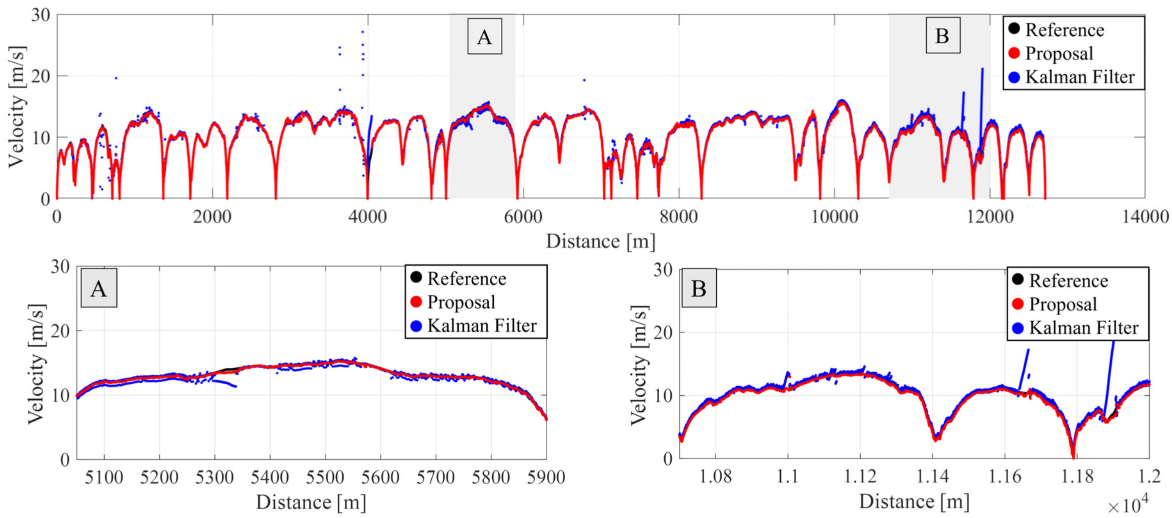

Fig. 10. Velocity estimation results for each method on route B.

a higher velocity estimation performance. Therefore, it is confirmed that the velocity estimation using the proposed method is more efficient than that using the conventional method.

However, in area B of **Fig. 9**, the proposed method produces an error in the estimated value. It is considered that the proposed method is insufficient for GNSS multipath determination. This is due to the dilemma in the parameter settings of the proposed method. If the time-series data used to optimize the velocity estimation are extended, the GNSS multipath determination performance will increase. However, the effect of the cumula-

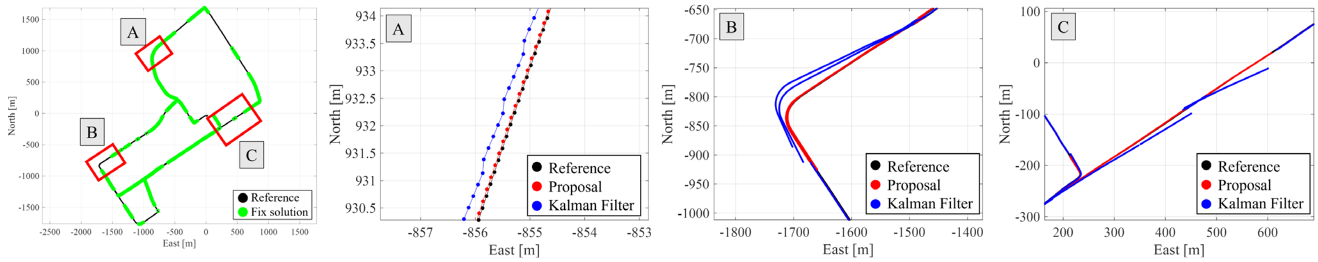

Fig. 11. Position estimation results for each method on route A.

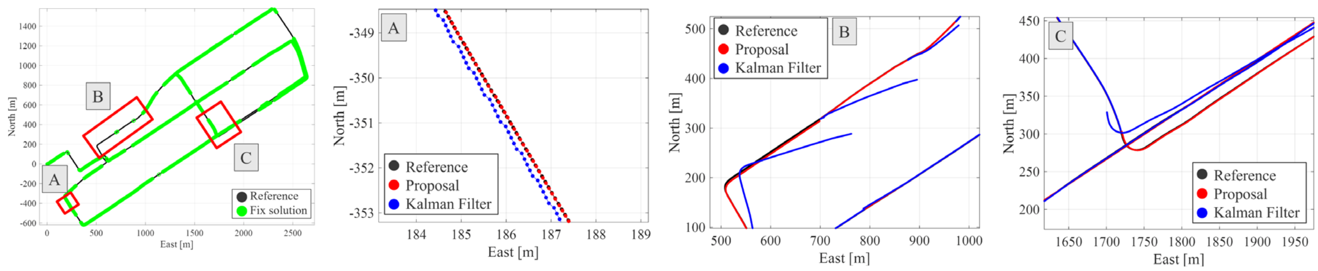

Fig. 12. Position estimation results for each method on route B.

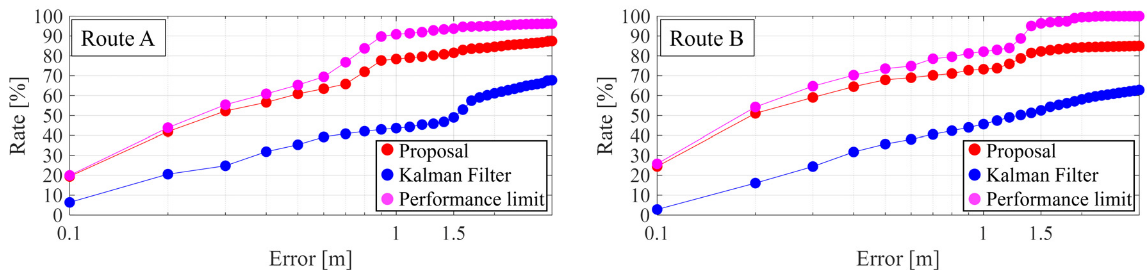

Fig. 13. Position estimation performance evaluation results.

tive error of acceleration integration is noticeable. Particularly in environments where the FIX solution is not available, the degradation of the pitch angle estimation performance also affects the velocity estimation. If the time-series data are shortened, the effect of the cumulative error is reduced. However, the GNSS multipath determination is insufficient. This is a limitation of the proposed method. It is necessary to vary the time-series data used for integration or improve the optimization method.

5.5. Evaluation Result: Position Performance

In this section, we evaluate the position estimation results. **Figs. 11** and **12** show the position estimation results for the proposed method and Kalman filter for each route. The results were divided into two types of environment. Location A in **Figs. 11** and **12** is an open-sky environment in which the FIX solution can be easily obtained. Locations B and C are surrounded by shields where the FIX solution cannot be obtained.

At location A, the results of the proposed method overlapped with the true position and exhibited little error. In contrast, the Kalman filter method continues to have an error of about 0.1–0.3 m. At locations B and C, the Kalman filter method has a larger error as the interval where the FIX solution cannot be obtained increases. The error in the direction of vehicle travel was significantly affected by the difference in the velocity estimation performance, and the error in the orthogonal direction was significantly affected by the error factor of the heading angle. In contrast, the proposed method provides position estimation results that are closer to the true position than the results obtained by the Kalman filter method. The proposed method estimates vehicle motion using long time-series data. This mechanism results in a high vehicle motion estimation performance and low errors in the direction of travel and in the orthogonal direction.

To statistically evaluate the position estimation results, **Fig. 13** shows the cumulative distribution function of the position estimation performance. In **Fig. 13**, the horizontal axis shows the position estimation error. The results obtained using the reference velocity in the dead reckoning model were also added as performance limits for the proposed method.

We focused on the percentage of time that the proposed method can estimate within 1.5 m, which is the lane-level accuracy. According to **Fig. 13**, for route A, the

Table 4. Evaluation results of processing time performance.

	Pitch angle		Acceleration error		Velocity		Total		Real time require [ms]
	Max [ms]	Mean [ms]	Max [ms]	Mean [ms]	Max [ms]	Mean [ms]	Max [ms]	Mean [ms]	
Route A	0.10	0.0061	0.46	0.24	0.092	0.010	0.52	0.26	< 20
Route B	0.095	0.0069	0.55	0.24	0.06	0.010	0.63	0.26	< 20

position estimation performance of the proposed method (81.6%) is 32.6% better than that of the Kalman filter method (49.0%). Similarly, for route B, the position estimation performance improved by 29.7% (82.3% for the proposed method and 52.6% for the Kalman filter method). These results indicate that the performance of the proposed method is superior to that of conventional methods. Compared with the performance limit of the proposed method, a predicted improvement of 12.1% for route A and 14.1% for route B remains. In other words, further improvements in the velocity estimation performance were shown to improve the position estimation performance.

In addition, this study used a dead reckoning model as the position estimation method. Various methods have been proposed for position estimation, including least-squares-based methods [16], particle filter-based methods [29], and global optimization-based methods [30]. We believe that these methods can be adapted to the proposed method to further improve location estimation performance.

5.6. Evaluation Result: Process Time Performance

In this section, we evaluate the processing time performance of the proposed method for speed estimation. Because the proposed method is intended for use in autonomous navigation, it must operate in real time. The conventional method [16], on which the proposed method is based, is implemented in robot operating system (ROS) [d] and has been verified to operate in real time. The proposed method is implemented on an ROS, similar to the conventional method [16], and is assumed to run in parallel. Therefore, it is necessary to confirm that the functions of the proposed method can work in real time.

The processing time required by the proposed method for each course is listed in **Table 4**. The proposed method has three functions: pitch angle estimation, acceleration error estimation, and velocity estimation. The processing time for each function is measured. The total processing time for all the processes was also measured.

Because the IMU operates at 50 Hz in this test, it must operate within 20 ms to operate in real-time. It can be confirmed that all functions of the proposed method are processed within 20 ms. In terms of total time, even if the maximum processing time is required, the processing is completed within the required time. Therefore, it was confirmed that the proposed method can operate in real-time.

6. Conclusion

Highly accurate location information is required for autonomous driving of mobile vehicles. This study investigated a new method of position estimation that targets lane-level accuracy in situations where the wheel speed of a mobile vehicle is unavailable. The proposed method adds velocity estimation to a conventional lane-level position estimation algorithm that requires the wheel speed.

The velocity estimation fuses GNSS Doppler and acceleration integration with the road gradient as a constraint. The main features of the proposed method are the handling of extended time-series data and consideration of vehicle motion. These features minimize the cumulative error owing to acceleration errors and improve the velocity estimation performance.

Evaluation tests in an urban environment showed that the proposed method improved the velocity and position estimation performance compared with the conventional method. From the evaluation test results, it is proved that the proposed method is effective because the position estimation performance improves with the velocity estimation performance.

However, it has also been confirmed that the effects of IMU acceleration and GNSS multipath errors remain, causing errors. Further mitigation of these effects is needed in the future.

The proposed method for correcting accelerometer errors is highly scalable. Instead of GNSS used in the proposed method, a camera or LiDAR can be used. These sensors estimate the accelerometer error using the pitch angle, relative movement of the moving object, and velocity. In particular, when LiDAR is used, it is possible to estimate the attitude angle accurately, and it is expected that the acceleration error estimation of the proposed method will be more accurate.

The acceleration error estimation performance of the IMU alone is also expected to improve when combined with gravity direction estimation and complementary filters. In addition, various methods have been proposed for position estimation, and we believe that adopting these methods can improve position estimation performance. We intend to investigate the velocity and position estimation methods using these methods in future work.

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Name:
Aoki Takanose

Affiliation:
Department of Intelligent Systems, Graduate School of Informatics, Nagoya University

Address:
Furo-cho, Chikusa-ku, Nagoya, Aichi 464-8603, Japan

Brief Biographical History:

2019 Received B.E. degree in Mechatronics Engineering from Meijo University

2021 Received M.E. degree in Mechatronics Engineering from Meijo University

2021- Ph.D. Student, Graduate School of Informatics, Nagoya University

Main Works:

- "Eagleye: A Lane-Level Localization Using Low-Cost GNSS/IMU," 2021 IEEE Intelligent Vehicles Symp. Workshops (IV Workshops), pp. 319-326, 2021.
- "High precision positioning using vehicle trajectories in urban environments (Improvement of RTK-GNSS by optimizing the initial conditions)," Trans. of the JSME, Vol.87, No.898, Article No.20-00157, 2021.
- "Improvement of Reliability Determination Performance of Real Time Kinematic Solutions Using Height Trajectory," Sensors, Vol.21, No.2, Article No.657, 2022.

Name:
Kaito Kondo

Affiliation:
Department of Mechatronics Engineering, Graduate School of Science and Technology, Meijo University

Address:
1-501 Shiogamaguchi, Tempaku-ku, Nagoya, Aichi 468-8502, Japan

Brief Biographical History:
2021- Department of Mechatronics Engineering, Graduate School of Science and Technology, Meijo University

Main Works:
• "RTK Availability Improvement Using Vehicle Trajectory to Determine Reliability of Integer Ambiguity," Trans. of the Society of Automotive Engineers of Japan, Vol.53, No.3, pp. 699-704, 2022.

Name:
Yuta Hoda

Affiliation:
Department of Mechatronics Engineering, Graduate School of Science and Technology, Meijo University

Address:
1-501 Shiogamaguchi, Tempaku-ku, Nagoya, Aichi 468-8502, Japan

Brief Biographical History:
2021- Department of Mechatronics Engineering, Graduate School of Science and Technology, Meijo University

Name:
Junichi Meguro

Affiliation:
Department of Mechatronics Engineering, Faculty of Science and Technology, Meijo University

Address:
1-501 Shiogamaguchi, Tempaku-ku, Nagoya, Aichi 468-8502, Japan

Brief Biographical History:
2008 Received Ph.D. from Waseda University
2008-2017 Researcher, Toyota Central Lab.
2017- Associate Professor, Meijo University

Main Works:
• Mapping, navigation, and positioning systems for automobile

Membership in Academic Societies:
• The Japan Society of Mechanical Engineering (JSME)
• The Robotics Society of Japan (RSJ)
• The Society of Instrument and Control Engineers (SICE)
• Society of Automotive Engineers of Japan (JSAE)
• Institute of Electrical and Electronics Engineers (IEEE)

Name:
Kazuya Takeda

Affiliation:
Graduate School of Informatics, Nagoya University

Address:
Furo-cho, Chikusa-ku, Nagoya, Aichi 464-8603, Japan

Brief Biographical History:
1983 Received B.E. degrees in Electrical Engineering from Nagoya University
1985 Received M.E. degrees in Electrical Engineering from Nagoya University
1986-1989 Advanced Telecommunication Research laboratories (ATR)
1987-1988 Visiting Scientist, MIT
1989-1995 Researcher and Research Supervisor, KDD Research and Development Laboratories
1994 Received Doctor of Engineering degree from Nagoya University
1995-2003 Associate Professor, Faculty of Engineering, Nagoya University
2003- Professor, Department of Media Science, Graduate School of Information Science, Nagoya University

Main Works:
• Media signal processing and its applications, which include spatial audio, robust speech recognition and driving behavior modeling

Membership in Academic Societies:
• Institute of Electrical and Electronics Engineers (IEEE) Intelligent Transportation Systems Society (ITSS), Member of the Board of Governors
• The Asia-Pacific Signal and Information Processing Association (APSIPA), Member of the Board of Governors