Abstract—This paper presents a 3Dimensional-GNSS (3D-GNSS) positioning technique, which is used for localization and mapping simultaneously (SLAM). The 3D building model becomes an important aid to many positioning techniques such as LiDAR and GPS positioning methods. In order to automatically create the accurate map in wide area, the precise position of mobile mapping platform is needed. However, GNSS positioning performance is severely degraded because of the effects of multipath and Non-Line-Of-Sight (NLOS) in the urban area. With the aid of 3D building map, the proposed 3D-GNSS distinguishes whether the received GNSS signal is transmitted as LOS or NLOS path, and can calculate the length of reflection path for the improvement of positioning error. To achieve highly accurate positioning in urban canyon, we further develop 3D-GNSS based integrated vehicle self-localization system, which is comprised of 3D-GNSS, inertial sensor and vision sensor. On the other hand, highly precise positioning needs the accurate 3D building map. Inspired by the idea of 3D-GNSS, this paper proposes to optimize the 3D building map by estimating the reflection of GNSS signals. In addition, the position of mobile mapping platform is estimated from our integrated localization system in the mapping stage. The experimental result demonstrates that sub-meter accuracy is achieved in both localization and mapping.

Keywords—GNSS; SLAM; vehicle self-localization; mapping; sensor fusion; 3D building map

I. INTRODUCTION

Vehicle self-localization in urban environment is an important and challenging issue in driving assistance and autonomous driving research activities. Both motion planning and vehicle cooperation need accurate localization, which is expected to distinguish the correct lane the vehicle occupied. The 3D building model becomes an important aid to many positioning techniques such as LiDAR and GPS positioning methods. If the more accurate 3D building map is obtained, the more accurate positioning solution can be estimated. In order to automatically create the accurate map in wide area, the precise position of mobile mapping platform is needed.

GNSS has shown the capability for vehicle localization in open sky field. However, the land vehicle typically has to operate in the urban area, where GNSS positioning accuracy is severely degraded because of the effects of multipath and Non-Line-Of-Sight (NLOS). Recently, many approaches of combination GNSS and 3D building map apply multipath and NLOS as additional measurements [1-5]. Our previous studies implemented a ray tracing method to track the transmitting path of GNSS signal [6-8]. With the aid of the ray-tracing method and 3D building map, we can distinguish that whether the received GNSS signal is transmitted by LOS or NLOS path and can calculate the length of reflection path. Our previous work demonstrated that the developed 3D-GNSS positioning method achieved high performance for localization in urban canyon environment [6-8].

Vehicle self-localization is expected to be sub-meter level in order to distinguish the correct lane the vehicle occupied [9, 10]. Following the idea of the integration of GPS and inertial navigation systems [11], we proposed to integrate inertial sensors and 3D-GNSS for vehicle applications as well [12]. The evaluation result indicated the inertial sensor can smooth the positioning trajectory, however, the combination of 3D-GNSS and inertial sensors still cannot satisfy the sub-meter accuracy requirement of autonomous driving. In addition to the inertial sensor and GNSS positioning, sensing techniques were also widely used for positioning. Lane markings are distinctive objects on road surfaces, which can be detected by vision sensor. These marking information there is able to aid the integration system [13-15]. In our previous work, we focused on the problem of vehicle self-localization in the most challenging environment, a city urban environment, and improves the positioning performance by integrating 3D-GNSS, inertial sensors and vision based lane detection [16]. This paper utilizes our integrated localization system to provide the position of mobile mapping platform for mapping.

To build highly accurate 3D building map, Mobile Mapping System (MMS) is one of the most popular approaches [17-19]. However, the expense of constructing 3D building map by MMS is high due to the expensive equipment and manual calibration. However, it is not so much difficult to obtain rough building footprint [20]. Rey-Jer and Bo-Cheng propose to reconstruct the 3D building model by integrating aerial LiDAR data with topographic maps [21]. The potential of the combination between aerial image and LiDAR data to refine the 3D building models is studied [22-24]. As for the increasing requirement of the higher accuracy 3D building models, a new classification method is also proposed to estimate accurate building roofs [25].

Inspired by the idea of 3D-GNSS, we proposes to optimize the 3D building map by GNSS measurements. In the urban canyon, GPS signal is often reflected by building surface.
These reflections are potentially capable of indicating the correct position of the buildings. By using a rough 3D building map, we apply it with a GNSS ray-tracing method to track the simulated reflection path of the NLOS signal. Theoretically, the length of observed reflection path and the length of simulated reflection path should be very similar. However, if the 3D map is not accurate, the difference between the observed pseudorange and simulated pseudorange will be recognized. To utilize this principle, the proposed method can estimate the true position of the wall on the 3D map. The feasibility of this idea has been proved in our previous research [26].

This paper proposes to use our integrated localization system for providing the position of mobile mapping platform in the wide area map rectification. In addition, the relationship between map quality and positioning result is discussed from the view of 3D-GNSS as well, which shows the significance of the accuracy of the 3D building model.

II. 3D-GNSS BASED INTEGRATED LOCALIZATION

The flowchart of the proposed system is shown in Fig. 1. In the integrated system, 3D-GNSS provides the global positioning result. The motion of vehicle is described via speedometer data from Control Area Network (CAN) bus, and heading direction from Inertial Measurement Unit (IMU). The lane keeping and lane changing behaviors are comprehended from the lane detection function. We use particle filter to integrate these information and the 2D lane marking map. The details have been published in our previous work [16].

A. 3D-GNSS

The integrated localization system considers the GNSS positioning result as the main information source. Generally speaking, GNSS positioning provides an estimation for localization, and the role of other sensors is to optimize the position around the GNSS result. A more accurate GNSS result makes it easier for the integrated system to achieve sub-meter accuracy. This paper proposes to utilize 3D-GNSS to reduce both the multipath and NLOS effects. We briefly describe the idea of 3D-GNSS in this section, while the details of 3D-GNSS have been published in our previous works [6–8]. Fig. 2(a) shows the flowchart of 3D-GNSS method. 3D-GNSS employs the candidate distribution algorithm to rectify the positioning error. Firstly, a set of position hypothesis, namely candidates, are distributed around the previous positioning result and the position given by commercial GNSS receiver. Next, 3D-GNSS generates the pseudorange simulation from each candidate position using the ray tracing, as shown in Fig. 2(b). By using ray tracing, both the satellite condition and the reflection delay can be estimated. The probability of each position hypothesis is evaluated based on the similarity between the pseudorange measurement and the pseudorange simulation. Finally, the 3D-GNSS provides the final rectified result by weighted averaging the positions of all the valid candidates. In this paper, we adopt the multiple satellite systems in 3D-GNSS, which includes not only GPS, but also GLObal NAviGation Satellite System (GLONASS) and Quasi Zenith Satellite System (QZSS).

B. Lane Keeping and Lane Changing Detection

The lane detection method used in this research is inspired by Aly’s work [27]. In the lane detection, a top view of the road surface is generated based on projective transformation. The Hough transformation and Random Sample Consensus (RANSAC) fitting are used to detect line boundaries. Thus, the position of the vehicle relative to the two line boundaries can be estimated. After the line boundaries are detected, each line is tracked by particle filter. Fig. 3(a) shows the line detection and tracking results in a lane changing process from frame $t$ to $t+2k$. From frame $t$ to $t+2k$, the position of the tracked Line-2 changes from the right side to the left side of the vehicle, which indicates the vehicle performs right-direction lane changing. Unlike the lane changing scenario, there is no line cross from

![Fig. 1. Flowchart of the proposed localization system.](image1)

![Fig. 2. (a) Flowchart of 3D-GNSS; (b) Example of ray-tracing.](image2)

![Fig. 3. (a) Detection of lane changing scenario. (b) Detection of lane keeping scenario.](image3)
one side to the other side of the vehicle in the lane keeping scenario, as shown in Fig. 3(b).

C. Sensor Integration for Localization

The multiple sensors are synchronized for positioning. 3D-GNSS, inertial sensor and the lane detection are integrated in a particle filter. The particle filter represents a posterior using a set of particles \( \{ \mathbf{x}_i^k : (x_{i,north}^k, y_{i,north}^k) \}_{i=1}^n \). \( \mathbf{x}_i^k \) is the 2 dimensional position of the particle, and \( i \) is the particle index, \( k \) is the time, \( n \) means the number of the particles. Each particle has an importance weight. The vehicle position is recursively estimated by three steps: prediction, correction and resampling. In the prediction, the heading direction and velocity of vehicle are used. The most important step is the correction, where the weight of each particle is evaluated. The distance between the GNSS positioning result and the particle \( i \) is consist of the longitudinal distance \( D_{i,GNSS,\text{longitudinal}}^k \) and the lateral distance \( D_{i,GNSS,\text{lateral}}^k \) by referring to the direction of the occupied lane. Therefore, the probability computed thanks to 3D-GNSS measurement \( p(\mathbf{G}_i | \mathbf{x}_i^k) \) is represented as follows:

\[
p(\mathbf{G}_i | \mathbf{x}_i^k) = p(\mathbf{G}_{i,\text{longitudinal}} | \mathbf{x}_i^k) \cdot p(\mathbf{G}_{i,\text{lateral}} | \mathbf{x}_i^k)
\]

This paper sets the value of \( \sigma_{\text{GNSS}}^2 \) as 9 m\(^2\) by tuning empirically. Fig. 4(a) demonstrates the probability of the particles estimated from the GNSS measurement. The particles around of the GNSS position have higher weighting than others. The lane detection provides the distance from the vehicle center to right and left lines \( [D_{\text{right}}, D_{\text{left}}] \). In addition, the distance from each particle to right and left lines \( [D_{\text{lateral, right}}, D_{\text{lateral, left}}] \) can be calculated from the prepared 2D lane marking map. The probability computed thanks to lane detection measurement \( p(\mathbf{V}_i | \mathbf{x}_i^k) \) can be calculated as follows:

\[
p(\mathbf{V}_i | \mathbf{x}_i^k) = \frac{1}{2} \{ p(\mathbf{V}_{i,\text{left}} | \mathbf{x}_i^k) + p(\mathbf{V}_{i,\text{right}} | \mathbf{x}_i^k) \}
\]

\[
p(\mathbf{V}_{i,side} | \mathbf{x}_i^k) = \exp \left( -\left( D_{\text{lateral, side}}^k \right)^2 / \hat{\sigma}_{\text{side}}^2 \right) , \text{side} \in \{ \text{right}, \text{left} \}
\]

where, probability \( p(\mathbf{V}_{i,\text{right}} | \mathbf{x}_i^k) \) and \( p(\mathbf{V}_{i,\text{left}} | \mathbf{x}_i^k) \) correspond to the right line and left line, respectively. This paper empirically sets the variance \( \hat{\sigma}_{\text{side}}^2 \) as 0.25 m\(^2\). Fig. 4(b) visualizes the probability \( p(\mathbf{V}_i | \mathbf{x}_i^k) \) estimated from the measurement of the lane detection. When the lane keeping is detected, the particles outside the occupied lane of the previous result, will be excluded in the calculation, and visualized as black dots in Fig. 4(b). It is important to note that the lane detection can sense the lateral position. It cannot perceive the position difference along the longitudinal direction. Therefore, we propose to integrate \( p(\mathbf{V}_i | \mathbf{x}_i^k) \) into \( p(\mathbf{G}_{i,\text{longitudinal}} | \mathbf{x}_i^k) \). Thus, the integrated probability is represented as:

\[
p(\mathbf{G}_i, \mathbf{V}_i | \mathbf{x}_i^k) = (1 - \gamma) \cdot p(\mathbf{G}_{i,\text{longitudinal}} | \mathbf{x}_i^k) + \gamma \cdot p(\mathbf{V}_i | \mathbf{x}_i^k) \cdot p(\mathbf{G}_{i,\text{lateral}} | \mathbf{x}_i^k)
\]

where, \( \gamma \) is the importance weight of the lane detection measurement. Fig. 4(c) visualizes the integrated probability of all particles by different colors. Comparing to Fig. 4(a), the high weighting particles are not around of GNSS positioning result, but appear in the correct lane. \( p(\mathbf{V}_i | \mathbf{x}_i^k) \) in (5) leads to this improvement. In addition, when the system detects lane changing, the operation for the particle exclusion follows the lane changing direction.

III. 3D-GNSS BASED MAPPING

Previously, Miura et al. have developed a GNSS positioning method to estimate accurate position using 3D building model and ray tracing method [6-8]. Ideally speaking, if the simulated transmitting path calculated by the ray tracing method is equal to the GNSS measurement, the 3D building model that used by ray tracing could be regarded as accurate as ground truth. As can be seen from Fig. 5, the building footprint of the 3D building model is gradually adjusted to the correct position based on the ray tracing estimation result. The objective of this paper is to correct a rough 3D building model into a level of sub-meter accuracy by using the GNSS measurements.

Fig. 5. Idea of applying GPS measurement to correct 3D building models.
A. GNSS Pseudorange Measurement

The pseudorange $\rho$ can be defined by the following equation.

$$\rho(t) = r(t, t-\tau) + c[\delta\tau(t) - \delta\tau_m(t-\tau) + I_p(t) + T_p(t) + \epsilon_{pr}\rho(t)]$$  \hspace{1cm} (6)

where $r(t, t-\tau)$ denotes the geometric distance from the satellite to the receiver. $\delta\tau(t)$ and $\delta\tau_m(t-\tau)$ denote the receiver clock bias and satellite clock bias, respectively. $c$ denotes the speed of light. $I_p(t)$ and $T_p(t)$ denote the ionospheric delay and tropospheric delay, respectively. $\epsilon_{pr}\rho(t)$ is pseudorange delay of reflection path such as multipath or NLOS delays. The NLOS reception arises when the direct path is blocked by the obstacle and the only received signal is reflection. The NLOS delay is always late came into the receiver. In the case of multipath effect there are two or more transmitting paths are received. It causes the ambiguous solution in the code tracking loop and this solution leads to a ranging of pseudorange error. For that reason, this paper only applies the measurements that suffered from the NLOS reception to correct the building footprint. To achieve this objective, it is important to distinguish the NLOS path from all the received signals. The simulated pseudorange is:

$$\hat{\rho}(t) = \hat{r}(t, t-\tau) + c[\hat{\delta}\tau(t) - \hat{\delta}\tau_m(t-\tau) + \hat{I}_p(t) + \hat{T}_p(t) + \hat{\epsilon}_{pr}\rho(t)]$$  \hspace{1cm} (7)

where the cap $\hat{}$ means the estimated value of the corresponding delay. The estimated geometric distance $\hat{r}(t, t-\tau)$ is calculated by the decided ground truth position of the receiver. All the delays are relatively modelable delays except NLOS delay $\hat{\epsilon}_{pr}\rho(t)$. This paper uses the Differential GNSS (DGNSS) technique to obtain the summation of delays $\hat{\delta}\tau(t)$, $\hat{I}_p(t)$ and $\hat{T}_p(t)$. The receiver clock offset is estimated to minimize the difference between the simulated set and the measured set. For the calculation of the NLOS delay, to track the signal travelling path from satellite to receiver is needed. This paper utilizes the direct path and a single reflected path. The calculation of NLOS delay is straightforward, and it is the signal reflection path minus the LOS path as shown in (8).

$$\epsilon_{pr}\rho(t) = R_{refl} - R$$  \hspace{1cm} (8)

The simulated pseudorange plays an important role to correct the building footprint of the 3D building model.

B. Building Footprint Adjusting Algorithm

Ideally speaking, the building footprint should be accurate if the simulated and measured NLOS pseudoranges are similar. In the other words, the difference between the simulated and measured pseudorange becomes the smallest when the footprint of the 3D building model and the true building model are matched. In this paper, the residue of the two kinds of pseudoranges is utilized as the evaluation value to estimate the true footprint of the building. The pseudorange residue can be expressed as:

$$d_{pr}^{m,j} = \rho^{m,j} - \hat{\rho}^{m,j}$$  \hspace{1cm} (9)

where $m$ and $j$ denote the $m$-th satellite and its reflection path which reflected by the $j$-th wall, respectively. The pseudorange residue of each wall $j$ can be expressed by

$$D_{pr} = \frac{1}{N_{refl}} \sum_{m} N_{refl} d_{pr}^{m,j}$$  \hspace{1cm} (10)

where $N_{refl}$ denotes the number of reflection paths by the $j$-th wall. The proposed building footprint adjusting algorithm is to adjust the building footprint to reduce the pseudorange residue $D_{pr}$ of each wall. The flowchart is shown in Fig. 6.

![Flowchart of the proposed algorithm.](image)

The proposed algorithm consists of three stages: 1) Pre-evaluation and finding one suspicious wall, 2) Roughly adjusting and 3) Precisely adjusting. Firstly, we select one wall which has detectable error using evaluation value $D_{pr}$ by the pre-evaluation. In this step, we calculate the pseudorange residue ($D_{pr}$) for each wall using only NLOS signals. Afterwards, we select one wall which has the highest pseudorange residue.

Secondly, we estimate approximate position of the selected wall. At the beginning of this step, we decide the direction to move the building footprint. For deciding direction, the sign of the pseudorange residue ($d_{pr}^{m,j}$) in (9) provides a hint. If the sign of the pseudorange residue is positive, it means that simulated pseudorange is longer than observed one. Namely, building footprint should be moved to the direction that the simulated pseudorange becomes shorter. Conversely, building footprint should be moved to the direction that the simulated pseudorange becomes longer. We adjust the wall along the decided direction 1m by 1m. In each adjustment, we compare the two pseudorange residues to decide whether the current adjustment is close to the true wall. When the local minimum of the pseudorange residue is found, the roughly adjustment stop and the roughly corrected position is decided.

Finally, wall is more precisely corrected around approximate position. The more wall candidates are distributed around the roughly corrected position with smaller interval, which is 0.05m in this research. The pseudorange residue of these candidates are evaluated. Finally, we conduct the curve fitting to decide the correct wall position using all the pseudorange residues corresponding to the rough adjustment and precise adjustment, as shown in Fig. 7. After correcting one wall, the same process is repeated and the proposed...
method selects a different wall. All the suspicious wall are corrected, a final 3D building models is outputted.

Fig. 7. Illustration of the wall adjusting procedure.

IV. EXPERIMENTAL RESULT

A. Experimental setup

We chose the Hitotsubashi area in Tokyo for experiments. Fig. 8 shows the rough 3D map for 3D-GNSS and accurate 2D map for integration. We used two kinds of data to construct the 3D map. The first one is the 2-dimensional building footprint, which is provided by Japan Geospatial Information Authority. The other one is the Digital Surface Model (DSM) data, obtained from Aero Asahi Corporation. The DSM data includes the height information of the building. The 2D map is generated from high resolution aerial images.

Fig. 8. 2D and 3D Maps used in this research.

In the experiment, a u-blox EVK-M8 GNSS model, a commercial level receiver was adopted. It can receive signals from multiple-GNSS (GPS, GLONASS, and QZSS). We placed the u-blox receiver on the top of our vehicle to collect pseudorange measurements. In addition, an IMU sensor (AMU-3002A Lite) and CAN data recorder were used to measure the angle attitude and the vehicle velocity, respectively. Moreover, an onboard camera was installed in the vehicle, which captured the front view images when driving. These images are the input of the lane detection algorithm. In addition, we manually distinguished the ground truth trajectory of our vehicle from these images, and manually decided the occupied lane for the result evaluation. The driving distance is approximate 1,500m in each test. In the vehicle self-localization, it is more important to distinguish which lane the vehicle is in compared to the positioning accuracy. Therefore, both the lateral error and the correct lane rate are employed to estimate the performance of the localization system.

B. Evaluation for vehicle localization

In order to understand the benefit of the proposed 3D-GNSS in urban environments, this paper compares the Weighted Least Square (WLS) GNSS-based integration and the proposed 3D-GNSS-based integration. Fig. 9(a) shows the positioning results of WLS-GNSS and 3D-GNSS using blue and red dots, respectively. The WLS-GNSS-based and 3D-GNSS-based integration in the same test are shown in Fig. 9(b), using green and yellow dots. The ground truth is represented by the cyan line. In Fig. 9(a), the blue dots corresponding to the WLS-GNSS result are randomly spread over a wide area. On the contrary, the 3D-GNSS is much more accurate compared to the WLS-GNSS. Moreover, the 3D-GNSS-based integration also indicates better performance than WLS-GNSS-based integration, which can be understood by comparing the green and yellow dots in the red rectangles of Fig. 9(b). Excepting for the GNSS positioning method, the two integration systems use the same algorithm. This proves that the more accurate the GNSS method is, the higher performance the integrated system has.

Fig. 9. Positioning results of WLS-GNSS, 3D-GNSS and integration systems.
of vertical lines are corresponding the three kinds of walls in the left figures. The blue points means the pseudorange residue obtained when we adjust the walls, and the black dash line is the cure fitting result. The experimental results in Fig. 10 and Table II demonstrate that the proposed method achieves the sub-meter accuracy regarding all the walls that reflected GNSS signals.

Fig. 10. Correction result of walls. (a) Visualization of the initial (green), true (brown) and estimated position (yellow) of the wall; (b) Process of adjusting the wall position using pseudorange residue (blue points).

D. Evaluation for map effect in localization

This section focuses on the discussion about the relationship between the 3D map and positioning result. In order to observe the effect of the wall position, we collect the static data for 30 minutes around of the interesting wall. In this period, the receiver received 7 signals from different satellites. Based on the ray tracing, we can know that one signal is NLOS, and reflected from the interesting wall. Because the 3D-GNSS method uses the average pseudorange similarity to decide weighting of each particle. In order to demonstrate the effect of the wall position, the weighting of each particle is only decided by the NLOS signal reflected by the interesting wall. The arrow mark in Fig. 11 is the ground truth position. Fig. 11(a) shows the weighting of particles related to the initial wall (green). After the map is corrected, the position of the wall is rectified as the yellow one, which is shown in Fig. 11(b). The weighting of particles related to the rectified wall (yellow) is also demonstrated in Fig. 11(b). The particles around the ground truth position have high weighting compared to Fig. 11(a). It means that the rectified building map makes the simulated pseudorange more closed to the observed pseudorange.

TABLE I. POSITIONING ERROR AND LANE RECOGNITION RATE OF DIFFERENT POSITIONING METHODS.

<table>
<thead>
<tr>
<th>Positioning Method</th>
<th>Positioning Error Mean (Meters)</th>
<th>Positioning Error Standard Deviation (Meters)</th>
<th>Correct Lane Recognition Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>WLS-GNSS</td>
<td>13.8</td>
<td>16.8</td>
<td>10.3%</td>
</tr>
<tr>
<td>WLS-GNSS &amp; IMU &amp; CAN</td>
<td>7.39</td>
<td>6.48</td>
<td>19.1%</td>
</tr>
<tr>
<td>WLS-GNSS &amp; IMU &amp; CAN &amp; Lane detection</td>
<td>4.36</td>
<td>4.54</td>
<td>27.8%</td>
</tr>
<tr>
<td>3D-GNSS</td>
<td>1.30</td>
<td>1.05</td>
<td>65.8%</td>
</tr>
<tr>
<td>3D-GNSS &amp; IMU &amp; CAN</td>
<td>1.19</td>
<td>0.92</td>
<td>72.4%</td>
</tr>
<tr>
<td>3D-GNSS &amp; IMU &amp; CAN &amp; Lane detection</td>
<td>0.76</td>
<td>0.78</td>
<td>93.0%</td>
</tr>
</tbody>
</table>

We repeat multiple tests along the driving route. Table I shows the quantitative comparison based on the multiple tests. As demonstrated in Table I, 3D-GNSS method also shows much better performance compared to WLS. About 65% of results are in the correct lane. Although 3D-GNSS cannot be directly used for vehicle self-localization, it has potential as the main source in the integration. After integrating with IMU and speedometer, the correct lane rate is increased and the mean error is improved to 1.2 meters. Table I indicates the integration of GNSS, IMU, speedometer and lane detection has 93% correct lane rate and sub-meter accuracy.

C. Evaluation for map correction

To demonstrate the performance of the proposed map correction algorithm, we estimate five walls to correct. In the experiments, the position of the receiver is provided by our developed localization method. The developed system can semi-automatically decide vehicle positions. The longitudinal position is controlled by the vehicle heading and velocity, and the lateral position in the lane is adjusted by the vision based lane detection function. The estimated walls have roughly 2 meters of error. The results applying the proposed algorithm are shown in Table II.

TABLE II. Location error of the target wall before and after correction.

<table>
<thead>
<tr>
<th>Wall No.</th>
<th>Initial error (meter)</th>
<th>Error after correction (meter)</th>
<th>Improvement (meter)</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. 1</td>
<td>2.739</td>
<td>1.042</td>
<td>1.697</td>
</tr>
<tr>
<td>No. 2</td>
<td>2.314</td>
<td>0.866</td>
<td>1.448</td>
</tr>
<tr>
<td>No. 3</td>
<td>1.398</td>
<td>0.391</td>
<td>1.007</td>
</tr>
<tr>
<td>No. 4</td>
<td>1.057</td>
<td>0.527</td>
<td>0.53</td>
</tr>
<tr>
<td>No. 5</td>
<td>1.438</td>
<td>0.645</td>
<td>0.793</td>
</tr>
<tr>
<td>mean</td>
<td>1.789</td>
<td>0.694</td>
<td>1.095</td>
</tr>
</tbody>
</table>

In addition, the detail of evaluation results of two walls are shown in Fig. 10 as examples. The brown wall is the ground truth wall positioning, which is provided by Measurement Company. The green one is the rough wall position, and yellow one is the corrected wall. In the right figures, the colors
In addition to discuss the weighting of particles, we discuss the relationship between the map and positioning result in terms of the positioning result. We plot the two positioning results in Fig. 12(a), which are calculated using the initial and rectified maps. The positioning error of two results are represented by blue and red color, respectively. It is obvious that the corrected map reduces the positioning error. Fig. 12(a) demonstrates the other point that the positioning error is improved more after $2.738 \times 10^5$ GPS time compared to before $2.738 \times 10^5$. The reason is that the total number of satellites is decreased after $2.738 \times 10^5$. In the whole experiment, one NLOS always reflected from the interesting wall. It means that this NLOS makes more contribution after the time $2.738 \times 10^5$. If the simulated pseudorange is more correct, the positioning error could be reduced more.

V. CONCLUSIONS AND DISCUSSIONS

As the rise of autonomous driving, the discussion of the aid of 3D building model to vehicles localization becomes a popular topic. Instead of LiDAR, this paper initiates the first idea of utilizing GNSS measurements to do the SLAM. The main difference between the famous LiDAR SLAM and our proposed 3D-GNSS SLAM is our method requires an initial 3D building model. The 3D map allows the ray-tracing to simulate the reflection path of the satellite signal. The ray-tracing result is informative to reduce the multipath and NLOS effects to rectify the localization result. The result from the 3D-GNSS can be optimized using other sensors, including inertial and vision sensors. If the positioning result becomes very accurate, it could be used to indicate where the GNSS signal is collected. Interesting part is that we can utilize the receiver position to evaluate if the simulated signal reflection path is similar to the measured distance (namely pseudorange measurement) or not. By adjusting the building location, the simulated reflection path is also changed. The accurate building location hence can be found until the simulation matched the measurement.

However, the proposed 3D-GNSS SLAM has an inevitable defect. It requires the building is able to reflect the satellite signal. If there is no NLOS signal reflected from the building, the building cannot be optimized by our proposed SLAM.

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