Evaluating Navigation Performance of Elastically Constructed HD Map with Multi-Sensor Fusion Engine System

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KEY WORDS: LiDAR, High-Definition Map, Kalman Filter, Positioning, Navigation, and Timing, point cloud, direct and indirect evaluation method.

ABSTRACT:

In response to the rapid development of autonomous vehicles and the increasing demand for HD maps, the conventional mapping processes following HD maps guidelines require significant manpower and time resources. Therefore, we propose flexible procedures and methods for HD maps creation, aiming to reduce cost expenditure by employing diverse source of ground control point, sensor data collection, and mapping algorithm. This approach accelerates the production speed and capability of HD maps. In this study, we select Taiwan's National Highway No. 8 as the trial field for the elastic HD map construction method, and equipped with autonomous vehicle-grade GNSS, IMU, and LiDAR systems. We align the constructed-map data to the global coordinate system, in order to realize the concept of control point cloud map. To assess the assistance and correction capabilities of HD maps in autonomous vehicle navigation systems, we conduct accuracy evaluation through both direct and indirect methods, and analyse the strengths and weaknesses of each approach. The analysis result demonstrates that the elastic method-built HD maps not only meet the mapping accuracy requirements specified in the HD maps verification and validation guidelines, but also assist autonomous vehicles in realizing positioning, navigation, and timing with “where in lane” level (0.5 meter) accuracy.

1. INTRODUCTION

Advanced automotive manufacturers in Europe, the United States, and Japan have been actively investing in the development of autonomous driving map information. Currently, many foreign countries prioritize the development of maps for highways and expressways (Massow et al., 2016). The main reason for this focus is that highways and expressways have lower complexity compared to urban roads in terms of road infrastructure. Additionally, when autonomous vehicles operate on highways and expressways, they face relatively straightforward situations such as maintaining distance from the preceding vehicle and being aware of lane-changing vehicles.

However, the establishment of High-Definition (HD) maps for highways in Taiwan requires the submission of a traffic maintenance plan for approval by the Highway Bureau, which involves deploying control points and conducting data collection. This conventional map construction method not only wastes time and money but also raises safety concerns. To address these challenges, this study proposes the use of Unmanned Aerial Vehicles (UAVs) to capture orthogonal images for measuring virtual ground control points (GCP). The data collected from autonomous vehicle-grade Inertial Navigation System (INS)/ Global Navigation Satellite System (GNSS)/ Light Detection and Ranging (LiDAR) sensors, and are fused with Loosely Coupled (LC) framework and utilized for Simultaneous Localization and Mapping (SLAM). After referring and verifying the map accuracy with the HD maps guidelines (TAICS, 2021), the constructed HD map can be utilized as the control point cloud map for autonomous driving in positioning, navigation, and timing application. To validate the map navigation possibilities, we raised the LC-INS/GNSS/LiDAR/HD map integrated system to simulate the autonomous vehicle system, and pass through two accuracy evaluation process, expecting to reach “where in lane” accuracy (Stephenson et al., 2011). The level of the navigation accuracy is illustrated in **Figure 1**.

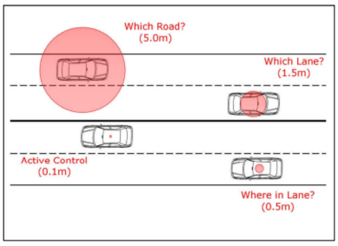

Figure 1. The position accuracy-based navigation level (Stephenson et al., 2011).

The contributions raised in this paper are listed in the following:

1. To decrease the cost of HD map construction and enhance the map production efficiency, the standard of the elastic map construction process is established, and two elastic HD map construction methods are raised, which is also the state-of-the-art extent for HD map construction.
2. To examine the autonomous vehicle navigation accuracy, direct and indirect evaluation methods are proposed, and analysis pros and cons of the approaches as well.
3. To put the elastic method-based HD map in practice, the map is fused with autonomous vehicle grade test system, and verify its navigation assisting capabilities and navigation accuracy level.

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To introduce the elastically HD map construction and validation structure sequentially, the reason why we raise this method is introduce in Section 1. In Section 2, it'll show the elastic map construction process. Furthermore, two primary elastic methods we propose for cost reduction will be demonstrated respectively. Section 3 explains and compares the concept of the direct and indirect evaluation methods. The elastic method built-HD map validation experiment is planned in Section 4, the results and discussions are made in Section 5. Finally, the conclusion is illustrated in Section 6.

2. ELASTIC METHOD FOR HD MAP CONSTRUCTION

In this section, it introduces the elastic method to construct HD map we proposed. As the construction of the HD map is money-costing and labour-wasting; therefore, we attempt to propose an elastic HD map construction architecture that can maintain accuracy while reducing costs, **Figure 2** is the overview of the process. The whole process refers to HD Maps operation guidelines (TAICS, 2021), verification and validation guidelines for HD Maps (TAICS, 2021), and HD Maps data contents and formats standard which published in TAICS (Taiwan Association of Information and Communication Standards). Among the process, the two primary elastic methods we propose for cost reduction is shown below, we'll introduce them sequentially in the following sections.

1. Diverse control point sources
2. Autonomous vehicle grade data with multi-sensor fusion engine system

To put this elastic HD map construction architecture into practice, the testing field takes place at the Taiwan National Highway No.8, with the total length of 15.5 km, as **Figure 3** shows. To reduce point cloud deformation caused by high-speed driving, and to adhere to the minimum speed specified by traffic regulations, the vehicle speed is maintained around 70 kph.

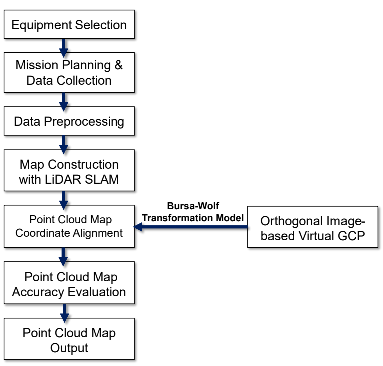


Figure 2. Architecture of elastic HD map construction.

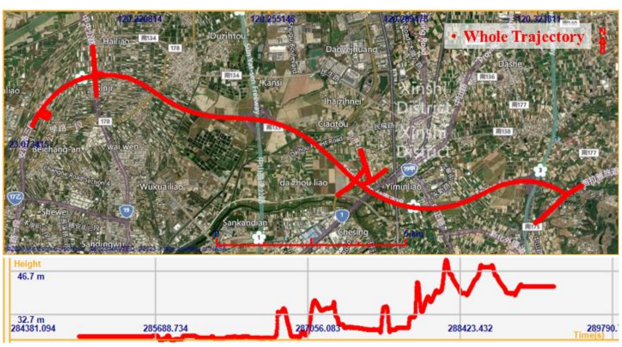


Figure 3. Trajectory of Taiwan National Highway No.8.

2.1 Diverse Control Point Sources

To set up physical GCPs, it takes lots of time and manpower, especially on the highway, it needs additional cost for traffic control and management to keep the transportation smooth and safe. Therefore, we try to raise the concept of virtual GCP as a more efficient way to set up GCPs. As we finish setting less physical GCP on the road nearby the highway, we utilize the UAV to collect the aerial photograph. After orthorectification process and aerial triangulation, it can measure the coordinates of the identifiable features from the orthogonal image, which are also existing and corresponding with the feature points in the scanned LiDAR data. In this paper, we select the midpoint of one end of the road markings as the virtual GCPs by every 250 m for both directions of the highway, as **Figure 4** shows.

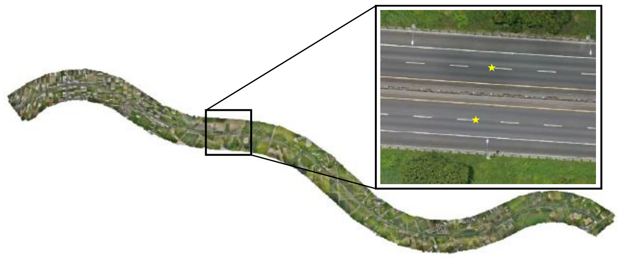


Figure 4. Orthogonal Image-measured Virtual GCP.

2.2 Autonomous Vehicle Grade Data with Multi-Sensor Fusion Engine System

For the data collection, instead of utilizing the Mobile Mapping System (MMS) attached with high-cost sensors for data collection, and the expensive commercial software for point cloud map construction. In this paper, we raise a multi-sensor fusion engine system to construct point cloud map, but with autonomous vehicle grade data. **Figure 5** is the framework of the LC-INS/GNSS/LiDAR fusion engine system for HD map construction. As the Tightly Coupled (TC) -INS/ GNSS fusion solution is computed and passes through time synchronization, Exterior Orientation Parameters (EOP) and Direct Georeferencing (DG) compensation (Mohamed et al., 2009), it not only provides initial guess information, including position, velocity, and attitude (PVA), for reorienting the LiDAR point cloud back to earth frame, but also serves as the prediction state for Adaptive Kalman Filter (AKF) (Aghili et al., 2016). Later on, to construct the map, it relies on more accurate PVA information. Therefore, it is able to conduct LiDAR point cloud scan matching by Normal Distribution Transform (NDT) with sliding window-based sub-map, and renew the PVA information for AKF state update. Finally, utilizing the updated PVA, the point cloud map can be constructed with LiDAR scan by scan continuously.

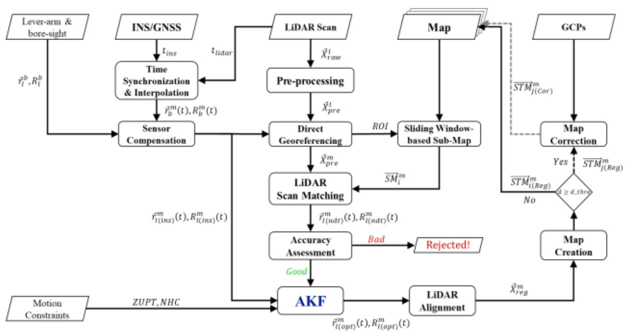


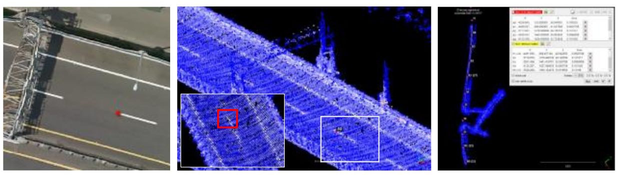
Figure 5. Framework of LC-INS/GNSS/LiDAR fusion engine system.

Although the point cloud map is already georeferenced to the world coordinate system, there may still be errors in the map data. Therefore, it is necessary to employ GCPs to constrain and refine the accurate positioning of the point cloud map. By combining the concept mentioned ahead, it can apply the virtual GCPs corresponding in both orthogonal images and point cloud map, to conduct Cartesian coordinate transformations with Bursa-Wolf Transformation Model (Deakin, 2006), as Equation (1) shows. To determine the precise seven-parameter values for coordinate transformation, including three translation, three rotation, and one scale parameters, we solve a set of observation equations based on Equation (1) by utilizing adjustment of indirect observation, listed in Equation (2). **Figure 6** shows the process of point cloud map coordinate adjustment. Finally, the point cloud map is well-restricted in the exact earth frame, as **Figure 7** shows.

$$\begin{bmatrix} X_Z \\ Y_B \\ Z_B \end{bmatrix} = (1+m) \times R(\theta_Z) \times R(\theta_Y) \times R(\theta_X) \times \begin{bmatrix} X_A \\ Y_A \\ Z_A \end{bmatrix} + \begin{bmatrix} T_X \\ T_Y \\ T_Z \end{bmatrix}$$
$$= (1+m) \times \begin{bmatrix} 0 & \varepsilon_Z & -\varepsilon_Y \\ -\varepsilon_Z & 0 & \varepsilon_X \\ \varepsilon_Y & -\varepsilon_X & 0 \end{bmatrix} \times \begin{bmatrix} X_A \\ Y_A \\ Z_A \end{bmatrix} + \begin{bmatrix} T_X \\ T_Y \\ T_Z \end{bmatrix} \quad (1)$$

where $X_A, Y_A, Z_A =$ the feature point position in the map
$X_B, Y_B, Z_B =$ the virtual GCP in orthogonal image
$T_X, T_Y, T_Z =$ the translation parameters
$R(\theta_X), R(\theta_Y), R(\theta_Z) =$ the rotation parameters
$m =$ scale parameter

$$L + v = B\hat{X} + d \quad (2)$$


(a) (b) (c)
Figure 6. Overview of the point cloud map coordinate adjustment process: (a) GCP in the orthogonal image; (b) GCP corresponding feature point in the point cloud map; (c) Relative accuracy analysis after coordinate adjustment.

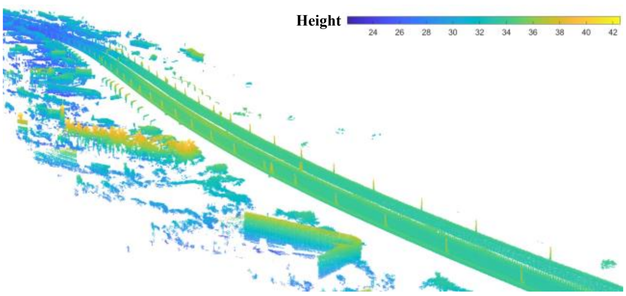


Figure 7. Elastic method-based Taiwan National HighwayNo.8.

2.3 HD Map Verification and Validation

Before publishing the map, the point cloud map shall undergo accuracy checks to ensure compliance with verification and validation guidelines (TAICS, 2021) and to verify the point density, relative plane and elevation deviation. After evaluation, the produced HD point cloud map meets the density requirements of grade 2 specified in the guidelines, with a point density ranging from 400 to 600 points per square meter, as **Table 1** shows.

Grade	Application Scenario (3D Accuracy)	Point Cloud Density (pt/m2)
Grade 1	Active Control (0.1 m)	2,500 - 10,000
Grade 2	Where in Lane (0.5 m)	400 - 2,500
Grade 3	Which Lane (1.5 m)	100 - 400

Table 1. Classification of point cloud density by grade (TAICS, 2021).

As for the relative plane deviation, it measures the static feature points' coordinates generated by data collected at different periods, and examined by every 1 km with at least 5 samples, as **Figure 8** shows. It turns out that the relative plane deviation falls within the guideline regulation (10 cm).

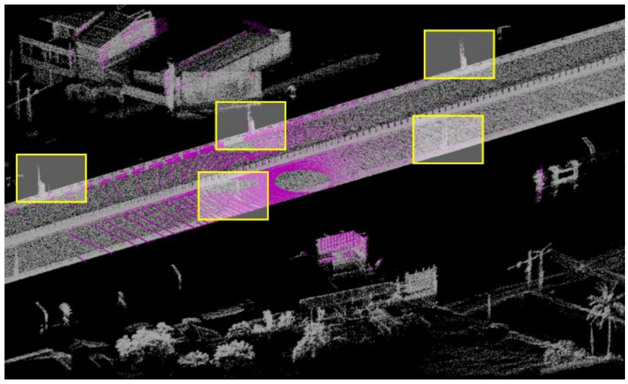


Figure 8. HD map relative plane deviation verification.

For the relative elevation deviation verification result is shown in **Figure 9**, we analyse the deviation by measuring the road points' coordinates generated from different scanning routes, and the validation is done by every 100 m with at least 5 samples must be inspected. The result shows that the relative elevation deviation is satisfied with the guideline threshold (10 cm). The future construction of the HD point cloud maps will continue referring and updating the operational specifications according to the guidelines.

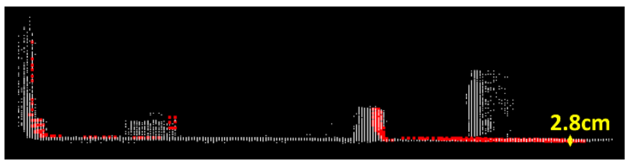


Figure 9. HD map relative elevation deviation verification.

3. METHODOLOGY

3.1 Navigation Performance Evaluation

3.1.1 Direct Evaluation Method: Figure 10 shows the flowchart of the direct method evaluation process. When performing direct method to evaluate navigation performance, a reference system is required. Therefore, during equipment preparation, the reference system and the autonomous vehicle system (referred as the test system in the following content) should be installed on the same platform for testing. However, even with high-levelled reference system, it possibly involves errors due to the characteristic of GNSS. In the context of high-speed movement on highway, the error of the along-track direction is particularly significant, the schematic diagram is illustrated in **Figure 11**. In **Figure** (a), the red point cloud represents the one after DG based on INS/GNSS fusion solution, while the white one is the prebuilt and verified HD point cloud map. Therefore, as the reference system provide the initial guess to initializes the LiDAR point cloud, the trajectory of the reference system is corrected by NDT scan to HD map matching to adjust the PVA, the adjustment result is illustrated in **Figure 11** (b). In this case, the test system can compare with the reference system by PVA solutions.

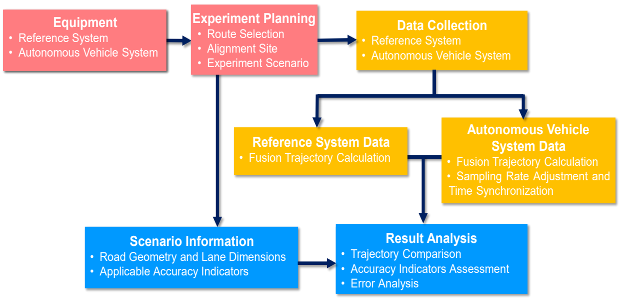
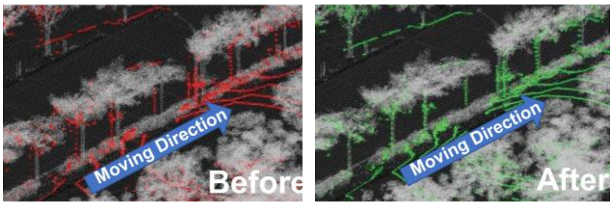


Figure 10. Flowchart of the direct evaluation method.



(a) (b)

Figure 11. Flowchart of the direct method evaluation process.

3.1.2 Indirect Evaluation Method: In **Figure 12**, it shows the flowchart of the indirect evaluation method. The main difference between indirect and direct method is that the reference results for comparison are either the HD map base map or reference point cloud collected by MMS grade sensors. Therefore, the evaluation field must construct the HD map or reference point cloud previously. During the evaluation, check points or road centrelines are selected in the field, and the coordinates of the check points obtained by the test system are compared with the coordinates of the corresponding check points in the reference point cloud or centrelines in the HD map. Therefore, it can indirectly verify the positioning accuracy of the test system.

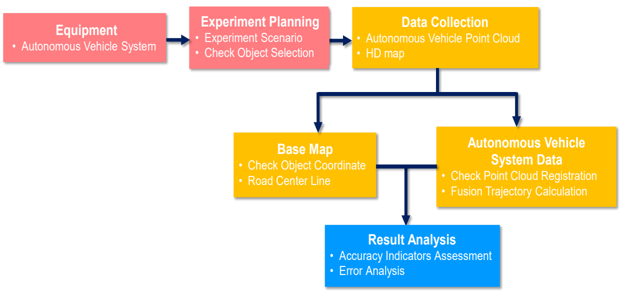


Figure 12. Flowchart of the indirect evaluation method.

Based on **Table 2**, the advantages and disadvantages of the two accuracy evaluation methods are evident. As direct method can clearly evaluate PVA information individually for better analysing the trajectory performance, but is much more expensive. While indirect method can validate the accuracy more visible, however this method isn't objective enough. In Section 5, the feasibility of using both direct and indirect methods for autonomous vehicle positioning accuracy validation will be analysed and assessed.

	Direct Method	Indirect Method
Pros	The verification method is well-established, and high accuracy systems have gained credibility.	Compare the results with ground survey accuracy check points (e.g., centerline data) for validation.
Cons	The cost of hardware and software is high, and there may not be enough space on autonomous vehicles to accommodate additional reference systems.	For indirect accuracy validation results, the onboard software should have the capability to select validation points.

Table 2. Pros and cons comparison between direct and indirect evaluation methods.

3.2 INS/ GNSS/ LiDAR/ HD Map Integrated System

For the framework of the test system, it can refer to **Figure 13**. As the Inertial Navigation System (INS) mechanization receives IMU's specific force and angular velocity data, and integrates them into PVA information. Instead of applying measurements mentioned ahead for EKF prediction, Madyastha et al. (2011) found out that due to the error state dynamics are linear, this makes it's more suitable to meet the KF's characteristic, and therefore output a more robust solution than using state vector. Hence, we form the state vector with error state vector, as Equation (3) shows.

With PVA information generated from INS mechanization and the elastic method-based HD map, it can provide reliable base map for LiDAR point cloud to realize NDT scan to map matching, which can correct the initial PVA guess. With this piece of information, it can gather with GNSS and motion constraints information back to EKF update (Chiang et al., 2023).

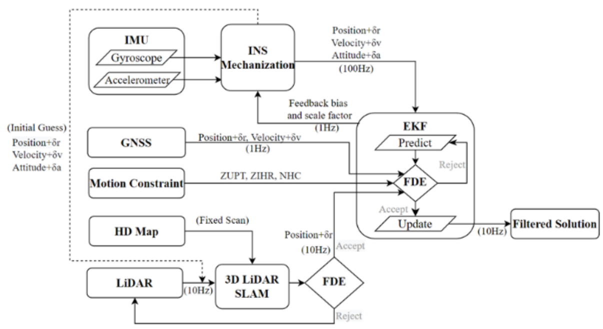


Figure 13. Framework of LC-IMU/GNSS/LiDAR/ HD map fusion algorithm.

$$x_k = [\delta r\ \delta v\ \delta \varphi\ \delta b_a\ \delta b_g\ \delta s_a\ \delta s_g]^T_{21\times 1} \quad (3)$$

where $\delta r =$ the position error vector
$\delta v =$ the velocity error vector
$\delta \varphi =$ the attitude error vector
$\delta b_a, \delta b_g =$ the bias error of accelerometer and gyroscope respectively
$\delta s_a, \delta s_g =$ the scale factor error of accelerometer and gyroscope respectively

4. EXPERIMENT

To verify the navigation-assisted performance of produced HD map for autonomous driving systems, the validation experiment selects 1 km of National Highway No. 8, starting from west to east with the speed around 70 kph. **Figure 14** exhibits the experiment filed, although it's an open sky scenario for GNSS, but it can tell that there are less features for LiDAR odometry in this scenario, especially in the along-track direction. Meanwhile, the dynamic vehicles may obviously affect the scan matching result in the along-track direction.

The sensors equipped for the experiment refer to **Figure 15**. The reference system we applied is the TC fusion solution of the iNAV-RQH IMU and NovAtel Pwrpak7D-E2 GNSS, calculated by the Inertial Explorer commercial software with postprocess smoothing algorithm. While the iNAV-RQH is equipped with the navigation grade IMU. For the test system, it applies the tactical grade NovAtel Pwrpak7D-E2 IMU/GNSS, and employs the GARMIN GPS18x LVC for time synchronization with Velodyne HDL-64E S3 LiDAR. The specifications of the IMUs are listed in **Table 3**, while the specification of the HDL-64E S3 LiDAR is arranged in **Table 4**.

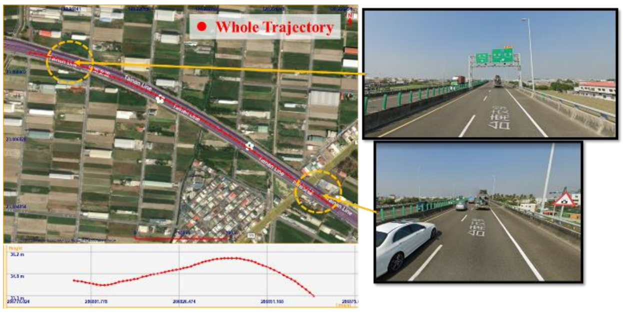


Figure 14. Experiment Scenario.

Figure 15. Equipment mounted on the autonomous vehicle.

	Gyroscope		Accelerometer	
	Bias Instability (deg/hr)	**Angular Random Walk ($deg/\sqrt{hr}$)**	**Bias Instability (μg)**	**Velocity Random Walk ($m/s/\sqrt{hr}$)**
iNAV-RQH	0.002	0.0015	10	0.005
Pwrpak7D-E2	0.8	0.06	100	0.025

Table 3. IMU specification of iMAR-iNAV-RQH-10018 and NovAtel Pwrpak7D-E2.

HDL-64E S3 Specification	Value
Maximum Measurement Range	120 m
Range Accuracy	±2cm (typical)
Field of View (Vertical)	+2° to -24.9° (26.9°)
Field of View (Horizontal)	360°
Angular Resolution (Vertical)	0.4°
Angular Resolution (Horizontal/ Azimuth)	0.08° - 0.35°

Table 4. IMU specification of Velodyne HDL-64E S3.

5. RESULT AND DISCUSSION

5.1 Direct Evaluation Result

The PVA results of the direct evaluation method are presented in **Table 5** to **Table 7** respectively. The analysis of position accuracy shows a horizontal Root Mean Square Error (RMSE) of 0.340 m and a three-dimensional (3D) RMSE of 0.348 m. Notably, the error in the East (E) direction is relatively larger, primarily resulting from the INS/GNSS fusion solution shows lower accuracy in along-track direction during high speed experiment, as the National Highway No.8. extends in the east to west direction.

Although the application of elastic method-based HD maps can correct the offset, the limited number of reference features in the along-track constrains the along-track extent of position correction. However, it still achieves navigation accuracy "where in lane" level. The RMSE for velocity in the three axes are 0.042, 0.025, and 0.012 m/s, with maximum errors of 0.112, 0.075, and 0.033 m/s, respectively. In terms of attitude, the RMSE in the East-North-Up (ENU) axes are 0.294, 0.028, and 0.083 degrees, with significant corrections observed in yaw and roll angles.

Error(m)	E	N	U	H	3D
Mean	0.278	0.115	0.059	0.301	0.307
Max	0.567	0.439	0.262	0.717	0.763
STD	0.511	0.173	0.112	0.539	0.550
RMSE	0.311	0.137	0.073	0.340	0.348

Table 5. Direct method: Position performance analysis.

Error(m)	E	N	U	H	3D
Mean	0.035	0.020	0.010	0.040	0.041
Max	0.112	0.075	0.033	0.135	0.139
STD	0.049	0.027	0.017	0.057	0.059
RMSE	0.042	0.025	0.012	0.049	0.051

Table 6. Direct method: Velocity performance analysis.

Error(deg)	Pitch	Roll	Heading
Mean	0.292	0.025	0.082
Max	0.352	0.056	0.097
STD	0.323	0.045	0.078
RMSE	0.294	0.028	0.083

Table 7. Direct method: Attitude performance analysis.

5.2 Indirect Evaluation Result

The validation site for the indirect method accuracy validation in the National Highway No. 8 is shown in **Figure 16** (a). In this field, 10 random areas with specific features for navigation performance verification were selected for validation, such as the light poles illustrates in **Figure 16** (b). **Table 8** presents the analysis results of the 3D position accuracy validation. In terms of RMSE, the ENU axis errors were 0.116, 0.054, and 0.041 m, 0.128 m in horizontal direction and 0.134 m in 3D. The maximum errors in the ENU axes were 0.199, 0.084, and 0.070 m, respectively, all of which comply with the navigation accuracy "where in lane".

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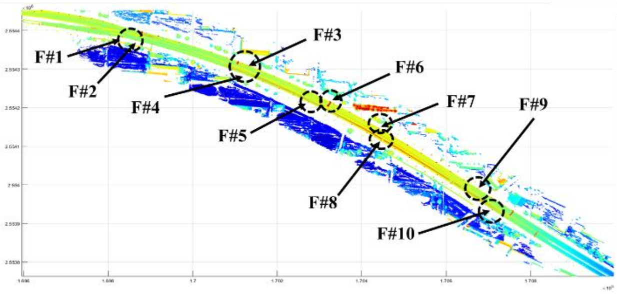
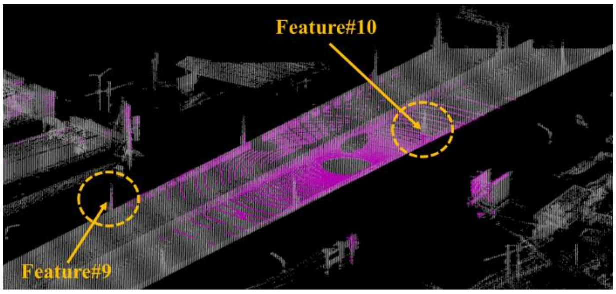


(a)



(b)

Figure 16. Indirect method accuracy analysis: (a) Verification site selection; (b) Schematic diagram of indirect method.

Error(m)	E	N	U	H	3D
Mean	0.109	0.046	0.036	0.123	0.118
Max	0.199	0.084	0.070	0.216	0.227
STD	0.118	0.056	0.043	0.131	0.137
RMSE	0.116	0.054	0.041	0.128	0.134

Table 8. Indirect method: Position performance analysis.

5.3 Summary

Based on the direct and indirect evaluation method from the on-road validation tests in the National Highway No. 8 test field, the accuracy achieved was “where in lane” level (less than 0.5 m). This not only demonstrates the feasibility of utilizing the HD point cloud map produced in this paper for on-road testing, but also indicates its navigation assistance capability for the autonomous vehicle level test system and realize the control point cloud purpose.

According to the accuracy evaluation processes mentioned ahead for both the direct and indirect methods, when conducting validations with other autonomous vehicles in the future, the validation approach will primarily focus on the direct method with the indirect method as a supplement. Besides, specific areas with HD maps will be designated as validation sites. The aim is to assess the along-track and cross-track accuracy of various scenarios to determine whether they meet the accuracy requirements based on vehicle size and road specifications. The errors will be compared with reference solutions to verify if they exceed the maximum error limits specified. Ultimately, the overall pass rate will be considered to determine whether the requirements are met with the HD maps guidelines and provide recommendations accordingly.

6. CONCLUSION

The application scenarios of elastic method-based control point cloud maps serve two purposes. On one hand, they serve as a fundamental base map, which not only allows for the extraction of features to build a neural network point cloud database but also facilitates accurate alignment of autonomous vehicle navigation in the world coordinate system. This ensures the establishment, updating, and increasing point density of the control point cloud maps. On the other hand, control point cloud maps can be treated as the additional navigation perception information for Level 3 autonomous vehicles and above, enabling the autonomous driving system to achieve “where in lane” level navigation accuracy.

The elastic methodologies proposed in this paper will continuously optimizing and keeping track with the state-of-the-art techniques. Hence, the objectives for the future work is listed below.

1. For larger and longer-range areas such as National Highway No. 1 or National Highway No. 3 in Taiwan, it is recommended to use a fixed-wing aircraft equipped with a measurement-type camera for aerial photography. With a constant Ground Sample Distance (GSD), higher flight altitudes can cover larger areas within the same aerial photography time.
2. For smaller and shorter-range areas, or when additional control points are required in specific local areas, the use of a copter for aerial photography can effectively reduce the cost of acquiring control points in the drone's imagery.
3. If aerial imagery is available throughout the survey area and discernible features are present, there is no limitation on the number of control points that can be added.

7. ACKNOWLEDGMENTS

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