Bending the Curve of HD Maps Production for Autonomous Vehicle Applications in Taiwan

Kai-Wei Chiang, Jhih-Cing Zeng, Meng-Lun Tsai, Hatem Darweesh, Pin-Xu Chen, and Chi-Kuei Wang

***Abstract*—Mapping technologies have improved over time, and autonomous driving techniques have advanced substantially over recent decades. High-definition (HD) maps are key for autonomous driving because of their accurate and rich interpretations of road scenes. HD maps provide information about road features, such as lane lines, centerlines, traffic signs, and traffic lights, to help autonomous vehicles navigate safely. HD maps have three major challenges: the standardization of the format of HD maps, conversion between map formats, and lack of techniques for automated HD map generation. These issues influence the costs of HD maps. Therefore, this article proposes strategies to overcome these challenges as well as control the cost with the support of the Ministry of the Interior in Taiwan. We established relevant HD map standards and guidelines to standardize the HD map production procedure. Additionally, we contribute to developing semiautomated HD map production tool to enhance the efficiency of HD map production. Another contribution is to develop HD map format conversion tool to satisfy the map requirement for different end-user. This project not only promotes the development of the Taiwanese autonomous driving industry but also increases its international competitiveness.**

***Index Terms*—HD map format conversion, HD map semiautomated production, HD map standardization, high-definition maps (HD maps).**

I. Introduction

INTELLIGENT unmanned vehicles have evolved rapidly in recent years, and the development of autonomous vehicle is especially the trend that carries the world before one. The Society of Automotive Engineers proposed categorizing autonomous driving systems into six levels of intelligence [1]. L4 (high automation) or L5 (full automation) must be achieved to produce autonomous vehicles that no longer require human intervention. Three main challenges must be overcome to realize full automation. First, autonomous vehicles must accurately know navigation-related information, particularly their position. Second, the limited sensing capabilities of mounted sensors due to occlusion or distance must be overcome. Third, autonomous vehicles must communicate with other vehicles to ensure safety. To achieve L4, a car must (at a minimum) accurately determine its position and drive in the correct lane. Unfortunately, positioning errors occur in urban areas because global navigation satellite system (GNSS) signals are contaminated due to multipath interference or non-line-of-sight reception [2]. In addition to sensors on the vehicle, including cameras, light detection and ranging (LiDAR) equipment, GNSS equipment, and inertial navigation systems, a map containing navigation information and reliable and robust environmental information is essential for autonomous driving. The autonomous vehicle must be able to make driving decisions and ensure driving safety through map feedback while driving. An improvement on conventional two-dimensional (2-D) electronic maps, modern high-definition (HD) maps can provide navigation information with true scales in the real world and in 3-D space. Moreover, HD maps are also sufficiently detailed, with planar and vertical accuracy of 20 and 30 cm, respectively, in 3-D space [3].

Some researchers have claimed that HD maps are unnecessary for autonomous driving because navigation can be completed solely using integrated sensors and artificial intelligence (AI) [4]. These can be used to operate a vehicle based on sensing information and control system without the use of a map; however, sensors still have limitations, including in their sensing range and performance, despite recent improvements in AI techniques. By contrast, the information in conventional maps, such as in feature, semantic, or object maps, is insufficient for realizing an optimal driving strategy with current road conditions, and vehicles using only conventional maps have difficulty meeting the safety and comfort requirements of commercial autonomous vehicles. On the contrary, HD map can assist information not only for navigation but also apply for collision avoidance. The development of obstacle recognition and tracking has been realized based on an integrated HD map and deep learning algorithm. Owing to the high accuracy of HD map, it is more efficient to classify different objects based on point cloud data [5]. In addition to point cloud data, the fisheye images are sufficient to identify the obstacles that occur in all directions. If the ratio of the detected area between two consecutive images is greater than a certain value, the obstacle will be identified [6]. Therefore, it is possible to implement integrated different obstacle detection methods with HD map to improve the performance. Numerous HD map format standards are used to handle differences in mapping methods and content as well as to increase the compatibility of maps used by various types of autonomous vehicles, such as OpenDRIVE, NDS, Autoware, International

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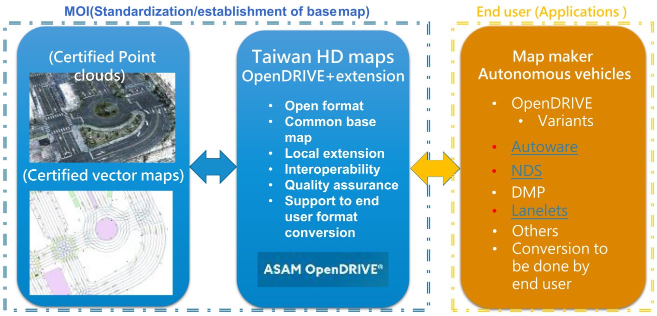


Fig. 1. Scope of HD maps in Taiwan [13].

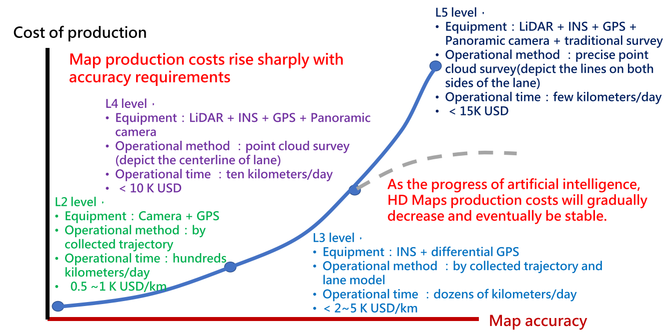


Fig. 2. HD map production cost curve.

Organization for Standardization (ISO) TC204/WG3, ADASIS, SIP-adus, and others. Interoperability between various automotive manufacturers or autonomous vehicle companies can be facilitated by following general guidelines for generating maps, including for data collection, map attribute definitions, and map format. Therefore, it is essential to establish a unified HD map format standard, which cannot only ensure the interoperability of all produced maps, but also control HD map production costs through standardized procedures.

After the establishment of related standards and guidelines, it is necessary to consider how to generate HD map efficiently. Nowadays, several researches focus on extracting road map based on remote sensing images by using deep learning algorithms. Ghandorh et al. [7] proposed to combine semantic segmentation and road edge detection based on high-resolution satellite images to improve the performance of road extraction. Similarly, Chen et al. [8] proposed implementing multiple lightweight U-Net models to realize the road segmentation. In addition to using remote sensing images, it is common to extract roads based on point cloud collected by mobile mapping systems (MMSs). Since point cloud benefits from accurate geospatial information, it takes advantage of road surface extraction based on the characteristic of point cloud, such as geometry and intensity [9], [10], [11]. Furthermore, the other road features, such as traffic lights and traffic signs, can be well extracted based on point cloud [12].

In addition to an evaluation of the HD map format standards and the map production method, data collection and end-user requirements must also be considered. The scope of HD map established in Taiwan is presented in Fig. 1 [13]. After data collection, the data are verified for vector map generation, and the map accuracy and attributes are assessed by a certified third party. Taiwan HD maps are regarded as unified and intermediate maps; end-users such as map makers or autonomous vehicle companies can convert these maps into other supported map formats based on their needs. The ability to convert maps has improved business and increased corporate investment.

In summary, several factors influence the costs of HD maps production, including accuracy requirements, formats, standards, production scale, business models, and related policies and regulations. Reducing production costs while maintaining quality and respecting relevant regulations is challenging. The curve in Fig. 2 indicates the map production costs for different autonomous vehicle levels; the costs are affected by the equipment, operational method, and execution time required for each level. However, as AI continues to improve, HD map production costs will gradually decrease and eventually stabilize. Strategies for reducing the cost of HD map production are as follows:

1) Standardize HD maps.
2) Standardize the data collection, production, and verification procedure.
3) Automate verification procedures.
4) Automate production tools with AI.
5) Design automated and versatile format converters.
6) Design versatile collecting method.
7) Implement data sharing.
8) Design an infrastructure production system.

With the support of Taiwan's Ministry of the Interior (MOI), we proposed strategies including the publication of related technical guidelines and HD map format standards, recommendation of steps for HD map production, establishment of flexible data acquisition and mapping services, stipulation of verification procedures, and development of tools for both format conversion and HD map production.

This article is organized as follows: Section II details the proposed strategies for reducing the cost of producing HD maps. Section III describes the current state of HD maps in Taiwan. Finally, Section IV concludes the article.

II. Proposed Strategy

Practical strategies for reducing the cost of producing HD maps are proposed in this section.

A. Published Technical Guidelines and Standards

The concept of the local dynamic map (LDM) was first proposed by Bosch in 2007. In LDM, a four-layer model describing road scenarios is adopted. The layers are divided by the frequency of changes in their elements. The first layer comprises permanent static data, including data on the road topology; road junctions; and the presence of traffic lights, traffic signs, or other static objects. The second layer comprises transient static data, such as construction or temporary traffic control information. The third layer comprises transient dynamic data (i.e., data that persists briefly), such as current congestion and traffic conditions or the phase of a traffic signal. The final

TABLE I
RECOMMENDED HD MAP FORMATS FOR AUTONOMOUS DRIVING APPLICATIONS [15]

Format	Purpose
LAS 1.2 or LAZ (compressed form of LAS)	Point cloud data capture for identification, extraction, and modeling of terrain and key features
OBJ	Good for representing the terrain and 3-D objects such as buildings
OpenDRIVE	Good for describing track-based road networks
ESRI shapefile	A portable format good at representing a wide range of specific key features and their attributes

TABLE II
HD MAP SELECTION CRITERIA [16]

HD Maps selection criteria (Scale: 1=bad;5=good)				
Criteria	Vector map format	OpenDRIVE	Lanelet2 (OSM XML)	NDS
Ease of creation	3	1	4	2
Tools	3	4	3	4
Adoption of format	1	4	2	5
Relation to production systems	1	3	1	5
Expressiveness	2	4	3	5
Interchangeability	2	3	3	2
Accessibility	2	4	5	1
Total	14	23	21	24

layer comprises data about highly dynamic entities, such as pedestrians or other vehicles, or data from sensors [14]. Because the map for autonomous vehicles comprises static high precision map information, dynamic environmental information, traffic data, and moving object data, LDM was used as a reference for designing Taiwan's HD maps architecture.

A report published by Ordnance Survey (OS) and Zenzic in England made recommendations for HD map format standards and related applications (Table I) [15]. These recommendations had three main aspects. For the data collection, point clouds are typically used for map generation data collected through surveying due to the high accuracy and detail of point cloud methods. The LAS format is a superior point cloud data format because it is sufficiently efficient for data processing and is compatible with a variety of equipment. For vector maps, the OS report suggested adopting the OBJ and SHP formats because the content and attributes of HD maps can be more completely described in these formats. For the HD map format standard, the OS report recommended using the OpenDRIVE or OpenSCENARIO format standards because these map format standards are open. Moreover, private companies and the British government are committed to constructing virtual autonomous vehicle systems and HD maps for testing. The OpenDRIVE format is suitable for describing the relationship among road networks and various types of road objects to simulate the operation of an autonomous vehicle in the real world. On the other hand, Autoware Map Data and Formats working group evaluated different HD map format standards based on feasibility criteria (Table II) [16]. The NDS format standard seems to have superior performance, but it is relatively inaccessible. Therefore, OpenDRIVE and Lanelet2 (OSM XML) were selected as the HD map format standards in Taiwan.

TABLE III
ACCURACY REQUIREMENT OF HD MAPS [17]

	Total error budget (map + vehicle) [meter 2sigma]	Map error [meter 2sigma]	Vehicle positioning error [meter 2sigma]
WHICHLANE	1.5	0.5	1.0
WHICHINLANE	0.5	0.2	0.3

TABLE IV
ACCURACY REQUIREMENT OF HD MAPS

HD maps absolute accuracy (localization support)		
	Horizontal	3-D
Taiwan	20 cm	30 cm
Japan	25 cm	35 cm
Korea	25 cm	35 cm

In additional to HD map format, the accuracy of HD map also needs to be considered. A safety report about vehicular navigation [17] reported that the error budget, including both map and positioning error, must at least meet the "WhereInLane" standard; that is, 0.2 m of map error and 0.3 m of positioning error (Table III). The accuracy requirements for HD maps in Taiwan and other similar Asian countries are presented in Table IV; the map accuracy regulations in Taiwan are consistent with those of Japan and Korea. The requirement of accuracy indirectly determines the surveying method, specification of equipment, and the surveying procedures.

As explained earlier, the production of HD maps requires unified guidelines and standards for controlling the quality of HD maps. Therefore, we have established related guidelines and standards, based on the HD maps architecture and recommended data format, for HD map operations, data content and format, and quality control. These guidelines and standards are also separated into static standards and dynamic standards based on the required situation.

1) HD Maps Operation Guidelines: Because HD maps must be accurate to ensure driving safety, HD map production must proceed according to carefully planned mapping procedures with certified instruments to control the quality of collected data. MMSs serve as an appropriate platform due to their mapping efficiency, and the recommended requirements of relevant sensors are presented in Table V. The complete mapping procedure comprises planning, data collection, and data processing (Fig. 3). The mapping plan, scope of the test field, road conditions, equipment, and surveying route must be carefully considered. Sensor behavior, including alignment, control point settings, and the quality of GNSS signals, must also be monitored during surveying. After surveying, data collected by mounted sensors, such as INS, GNSS, cameras, and LiDAR, are processed and verified for the subsequent production of an HD map.

2) HD Maps Data Contents and Formats Standard: The HD map data content and format standard was designed based on the OpenDRIVE 1.5 format standard with extensions for the unique

TABLE V
INSTRUMENT GUIDELINES FOR HD MAP PRODUCTION [18]

Instrument		Recommendation
RTK reference station and rover station receiver grade		Survey-grade multiconstellation and multifrequency carrier phase GNSS receiver
IMU	Grade	Details shown in Table VI
	Instability of gyroscope drift	
	Instability of accelerator drift	
IMU calibration		Must be done
IMU sampling rate		>100 Hz
POS results (without DMI, no GNSS outage)	Horizontal position accuracy	<3 cm
	Vertical position accuracy	<5 cm
	Pitch angle accuracy	<0.002°
	Heading angle accuracy	<0.005°
POS results (with DMI, during GNSS outage)	Horizontal position accuracy	<0.05% system drift rate
LiDAR calibration		Must be done
Camera calibration		Must be done
Point cloud density		>400 pt/m²
ZUPT frequency	Open sky area	1-min ZUPT per 10 min
	GNSS-hostile area	1-min ZUPT per 2 min
Ground control point aided		Details shown in Table VI
System alignment		Must be done at start and end

TABLE VI
IMU SPECIFICATIONS AND GROUND CONTROL POINT SETTINGS [18]

Grade	Instability of gyroscope drift	Instability of accelerator drift	Ground control point aided
Navigation-grade	0.001–0.1 deg/hr	50–100 μg	per 500 m
Advanced tactical grade	0.1–1 deg/h	100–300 μg	per 300 m
Medium tactical grade	1–10 deg/h	300–1000 μg	per 100 m
Other	>1 deg/h	>2 mg	per 30 m

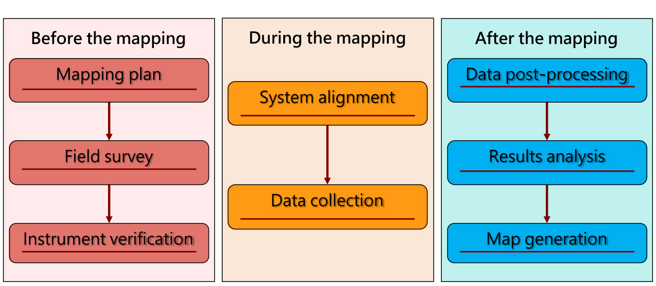


Fig. 3. Recommended mapping procedures for producing HD maps [18].

characteristics of Taiwanese roads. The content defined in this standard can be roughly divided into the categories of roads, lanes, road markings, traffic signs, traffic lights, objects, tunnels, bridges, and junctions. The detailed attributes are recorded in their corresponding layers. For example, the attributes defined

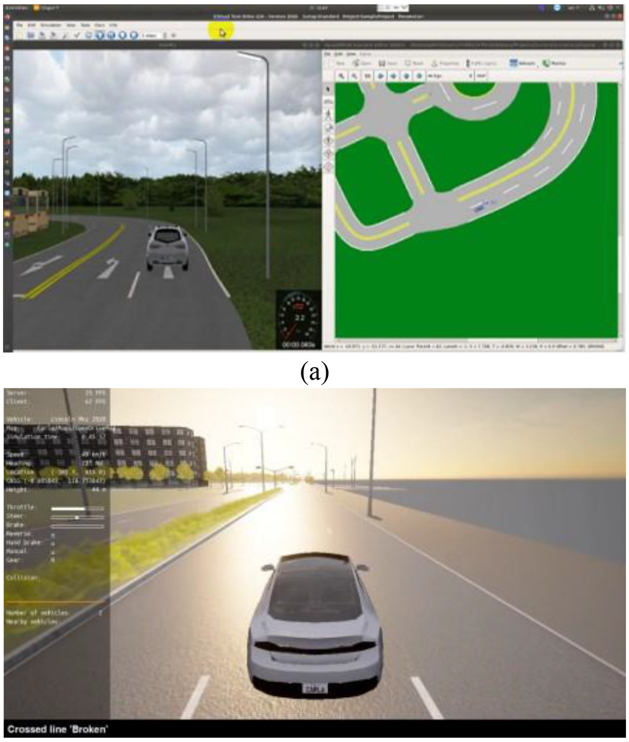
TABLE VII
EXTENSION PART IN HD MAP DATA AND FORMAT STANDARD [19]

Type	extension
Road	National highway
	Provincial highway
	Provincial highway
Lane	lowSpeed
	Barrier
	Inner shoulder
	Outer shoulder
	Island
	Bus parking
	Public utilities
Object	Deceleration
	drainCover
	manholeCover
	Hydran
	speedCamera
	redLightCamera
	trafficPole
	Delineator

in LaneCenterLine include an identification number (ID), predecessor ID, successor ID, startWaypoint, endWaypoint, and type. The extension is recorded in "userData" in the road layer. Table VII provides some examples of the Taiwanese extensions according to the format standard.

3) Verification and Validation Guideline for HD Maps: In addition to the mapping guidelines and map format standard, processes for accuracy verification and quality control for evaluating HD maps are required. These processes in published guidelines can be divided into two main categories [20]. The first category involves the verification of data collection quality, including verifications of control surveying, results of point cloud density and subsequent adjustments, relative accuracy of scanning strips, GNSS measurements, and the performance of trajectory. The second category involves the evaluation of the performance of the generated vector map. The attributes and content of the HD maps must conform to the HD maps data contents and formats standard, and the absolute accuracy of the map must be 20 cm planar and 30 cm vertically.

4) Simulator Verification: Real-world road scenarios are complex. Both the control systems and the maps of autonomous vehicles must pass rigorous and comprehensive tests. However, physical testing on real roads is costly, dangerous, and not necessarily reproducible [21]. Simulations are thus an alternative to real-world testing. Several resources and platforms for autonomous driving simulation have been developed. Virtual test drive (VTD) is a vehicle simulator that enables the creation, configuration, presentation, and evaluation of virtual environments for road-based and rail-based simulations. VTD is comprehensive and can generate 3-D content, simulate complex traffic scenarios, and even simulate either simplified or physically driven sensors [22]. Although VTD is versatile, it is a proprietary tool. By contrast, the Car Learning to Act Simulator is an open-source simulator for autonomous driving research. It supports the training, prototyping, and validation of autonomous driving models, such as for perception and control schemes [23]. The format of generated maps can be converted



(a)

(b)

Fig. 4. Simulation of autonomous driving with generated HD maps. (a) Simulation in VTD. (b) Simulation in CARLA.

into OpenDRIVE maps and loaded into these simulators to guarantee the stability of simulated driving tests and correctness of the map connection. Simulations of autonomous driving on the generated HD maps are presented in Fig. 4.

5) Related Dynamic Map Draft: The aforementioned published guidelines and standards are established for static maps. In addition to using these guidelines and standards, we also aim to determine drafts for related dynamic HD maps. Although the static HD maps have been generated, they require regular updates to reflect changes in the road environment and to ensure road safety. Regular update methods can be performed either through updates with a professional MMS or the use of a third-party platform that is equipped with the same specifications as an autonomous vehicle. The data acquisition, production, and verification of HD map updates by the professional MMS can follow the guidelines and standards mentioned in previous sections. The quality of data collected by third-party platforms is likely inferior to the data collected from the professional MMS; however, third-party platforms have substantially lower costs. Moreover, the quality of the results from third-party platforms can also be guaranteed by verification procedures and sensor fusion technologies for updating HD maps. We thus propose the "Operation and verification guidelines for HD maps updating – Permanent static data" to handle data acquisition and verification for dynamic data updates. The dynamic HD maps data contents and formats standard also defines events that may affect road driving or cause changes over time. This standard refers to international standards established by the European Telecommunications Standards Institute and ISO and

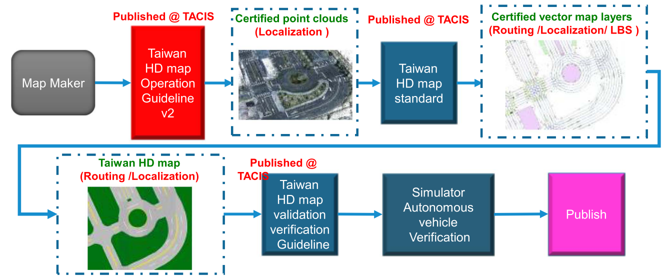


Fig. 5. Proposed steps for HD map production.

is used to evaluate the status of events, such as real-time traffic, parking, weather, and road condition, for autonomous driving. This dynamic HD maps data contents and formats standard can be combined with static HD maps to assist autonomous vehicles in decision-making during driving.

B. Proposed Steps for Producing HD Maps

The proposed steps for the entire process of producing HD static maps production (Fig. 5) to be conducted in accordance with the guidelines and standards for professional MMS described in previous sections. Mapmakers can follow guidelines to collect sensor data and then create maps based on the definitions in the format standard. After the generated map is verified and passes the simulation test, the HD maps are published for use by surveying services, research institutes, and autonomous vehicles. This procedure cannot only be implemented in HD map production but can also be adapted to HD map maintenance. Moreover, the simulator verification is used to evaluate whether the established guidelines and standards are practical and meet international standards. These established guidelines and standards can be continually revised and updated through feedback from mapmakers and end-users.

It is worth noting that since HD map is consisted of high-accuracy geospatial data, the whole procedure from data collection to map usage is control by the government to avoid the ethics issue.

C. Flexible Data Acquisition and Mapping Service

For data acquisition, the professional MMS and recommended mapping procedure can achieve a highly accurate base map for HD maps that require only low-frequency updating and maintenance. However, the frequency of HD maps updates is limited by the costs incurred in data acquisition, mapping, and generation of the HD map. Any change in the road environment, such as repainting a road marking or placing new traffic signs, will not be immediately reflected in the static base map. One feasible solution to this problem is implementing certified low-cost mapping payloads and mapping procedures with third-party sourcing for rapid or near-real-time dynamic updates. Changes in the physical features of the road are generally classified into three cases: physical feature removal, new physical feature insertion, and no change [24]. The detected changes are compared with the existing HD maps. If no feature exists in the HD map after searching within a certain range of

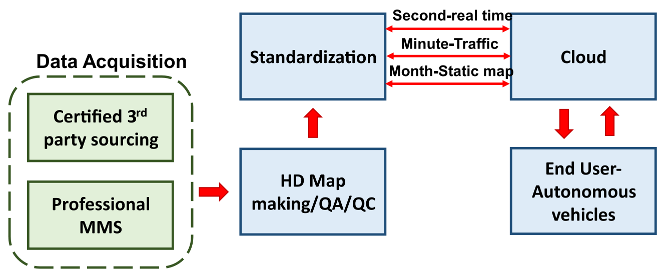


Fig. 6. Entire data acquisition and mapping process.

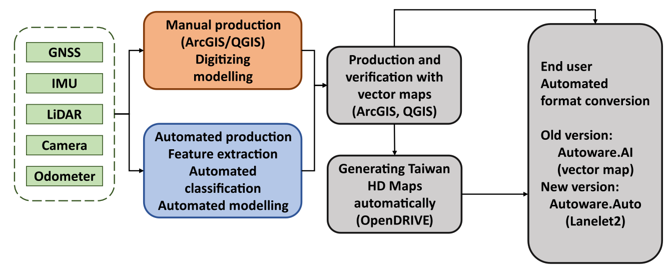


Fig. 7. Proposed semiautomated HD maps production procedure.

the changed location, the detected changes are determined to be an inserted feature. Misjudgments due to detection errors are inevitable; thus, crowdsourcing with voting is an efficient method of estimating the credibility of detected changes. For an insertion change, the change is approved only if the ratio of successfully detected to undetected features is greater than the threshold. For a removal change, the features around the location of the detected change must first be compared with the HD map due to the sensing limitations of the autonomous vehicle. If the distance between the target feature and the detected feature is lower than a given threshold, the case is determined to be one of no change; if not, it is determined to be a removal. However, this removed case must still be assessed through the voting method to determine whether the detected feature was removed.

After verifying the content and accuracy of the HD maps, these certified vector maps can be converted to a standard format. These HD maps are then published and uploaded to the cloud. End-users can download and use these maps for autonomous vehicles. The entire data acquisition and mapping process is presented in Fig. 6.

D. Automated HD Map Format Conversion Tool

Although the Taiwan HD map format standard is established based on OpenDRIVE with extension, the most common HD map format used by automotive companies is Lanelet2, which is the format of HD maps defined in Autoware. Therefore, an automated HD map format conversion tool could improve the efficiency and reduce the cost of converting the generated maps into HD maps usable by autonomous vehicles. We developed an automated HD map format conversion tool, the ASSURE mapping tool. This tool supports various map formats as input, such as OpenPlanner map (.kml), Google Earth map (.kml), OpenDRIVE (.xodr), Lanelet2 (.osm), and vector map (.csv). The supported output formats are OpenPlanner map, Google Earth map, and Lanelet2. Owing to the demand of automotive companies, we focus on the conversion to Lanelet2.

In OpenDRIVE, roads are built based on a reference line. All lanes are generated by a certain lateral distance from the reference line. OpenDRIVE map is defined in a local coordinate system for each road section. The road geometry is described by several types including straight lines, spirals, arcs, and parametric cubic polynomial according to the curvature of the road. Each lane is assigned ID according to the reference line in every road section. If the direction of lanes has the same direction as the reference line, lanes are assigned with negative ID. On the other hand, lanes also record the successor lane ID and predecessor lane ID to construct the connection of each lane. On the contrary, Lanelet2 is defined as drivable road segments without using a specify reference line. Therefore, the boundary of every lanelet is generated with a series of points which contain direction information. If the left border to lanelet_1 is identical to the right border of lanelet_2, the lanelet_2 is defined as left-adjacent to lanelet_1. According to the different definition, the principle task for conversion is to modeling the OpenDRIVE roads to create a series of point in each lane [25]. After grabbing the points of reference line, the point of the rest lane can be extended by the defined road width. The final step is to remodel these boundaries of lane to generate optimized border points.

E. Semiautomated HD Map Production Tool

An HD map production tool could significantly reduce labor and time costs. However, automation is imperfect, especially in complex road scenarios. We propose a semiautomated procedure for the final evaluation and revisions of generated HD maps (Fig. 7). Some features can be more efficiently created manually than automatically. The features of HD maps are produced manually or automatically in accordance with their characteristics. Automated production is suitable for features that can be modeled by an algorithm or are complicated to manually produce.

As noted in the previous section, the base map is the foundation for HD maps. Therefore, we developed a semiautomated HD map production tool to generate the road edge, lane line, and lane centerline; all are vital for autonomous vehicle control systems. Moreover, detection performance and recognition technologies have improved substantially with advances in computer vision and AI technology. Hence, our tool also handles the generation of traffic lights and certain traffic signs. The sensing data used in the production tool are position and orientation system, point cloud, and image data. The architecture of our production tool can be divided into parts for ground feature generation, such as road edge, lane line, and lane centerline, and parts for nonground feature generation, including traffic lights and signs.

1) Ground Feature Generation: A flowchart of ground feature generation is presented in Fig. 8. Because the target features belong to the ground point cloud, the nonground point cloud is first removed. We next downsample the point cloud to increase the efficiency of the algorithm. The key method in ground feature

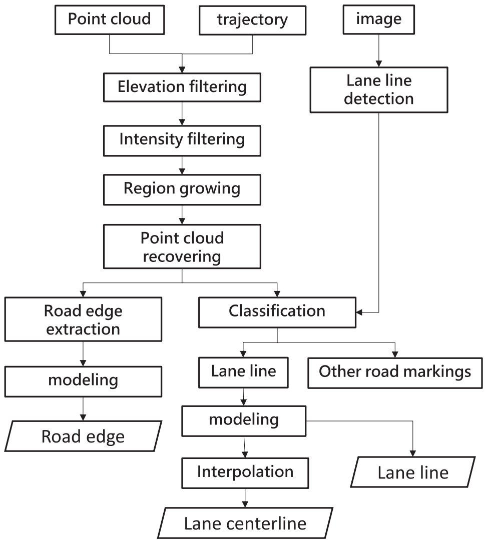


Fig. 8. Flowchart of ground feature generation.

generation is defining the road range. Typically, a curb structure is beside the road. Because the height of the curb is higher than the road surface, the point cloud is perceived as the location of road edge if the height difference is larger than a given threshold [9], [10]. Thus, the curb is a distinctive feature for determining the road location. Unfortunately, many roads lack curb structures. To adapt the architecture to various road scenarios, we implemented the region-growing algorithm proposed in [11] to extract the complete road range in a complex environment. The ground point cloud is separated into low-intensity and high-intensity point clouds by using an intensity filter. That is, the point cloud can be roughly distinguished into parts indicating asphalt road and parts indicating road markings. The region-growing algorithm is then used on the low-intensity point cloud. First, the initial point is randomly selected. Subsequently, the neighboring points are searched in a given radius. If the height difference between the searched point and the average height of all points in searched range is lower than a threshold, the searched point is determined to be part of the road surface. After the entire point cloud is searched, the road point cloud can be determined. Because the road range is approximately known, the road marking points on the road surface can be recovered from the high-intensity point cloud. The combination of road markings and road surface points represent the complete road range. Thus, the road edge can be defined directly.

The extracted road markings are clustered and classified into types, such as lane line, stop line, arrow, or text, based on their geometry. Although point clouds can accurately describe the geometry and position of features, they are inadequate for semantic information; visual data, namely images, are required. Therefore, the fusing of point clouds with images is widely used to improve road marking classification [26], [27]. Convolutional neural networks (CNNs) are commonly used in image detection and classification tasks. We propose using a CNN-based model to subdivide the extracted lane lines into types, such as white or yellow lines.

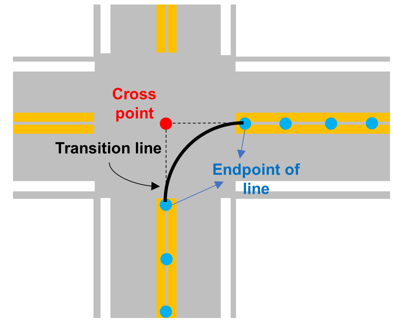


Fig. 9. B-spline and control points.

In addition to extracting the target road elements, modeling is vital for transforming the sensor data to the vector maps used in autonomous vehicles. Although the point cloud map can maintain the integrity and quantity of the raw sensing data, the point cloud itself is too large to upload or download with the limited data communications in autonomous vehicle. Thus, an appropriate representation for road geometry is essential for maintaining storage efficiency, usability, and map accuracy. Several road geometry modeling algorithms have been proposed. Among these, models using clothoids are thought to best represent road geometry because roads are often designed using clothoid geometry. Additionally, clothoids are particularly accurate for representing the path of a vehicle whose turning radius is a linear function of its distance traveled because the clothoid's curvature also changes linearly with arc length [28]. However, clothoid modeling is impractical for autonomous vehicles due to the complex calculations and substantial computational resources required. Moreover, clothoids are inherently defined as 2-D curves; they thus cannot represent 3-D road geometry when used alone. An alternative method of expressing road geometry is through spline curves. Several types of spline curves have been used to represent road geometry [29], [30], [31]. We implemented a cubic spline algorithm, which comprises a set of piecewise third-order polynomials, to model the road edge and lane line. This method has a simple, intuitive formula, and is sufficiently accurate. Because third-order polynomials are used to determine a relationship between each pair of points, a low-order polynomial function can precisely fit the data and can avoid the data instability (known as Runge's phenomenon) that may occur in high-order polynomial interpolations.

However, intersections do not have obvious features, such as lane lines on roads. If the transition line in an intersection is generated based on the cubic spline, the transition curve will not reflect the real driving behavior. Therefore, the cubic spline is replaced with the B-spline to handle the transition in the intersection. The control points for the B-spline are the endpoints of two arbitrary linking lines and their intersection point, and the ideal transition line can be created by adjusting these control points. An illustration of the B-spline and its control points is presented in Fig. 9.

The centerline is a 3-D virtual reference line that provides a guideline for autonomous driving. In [32], a prior centerline is

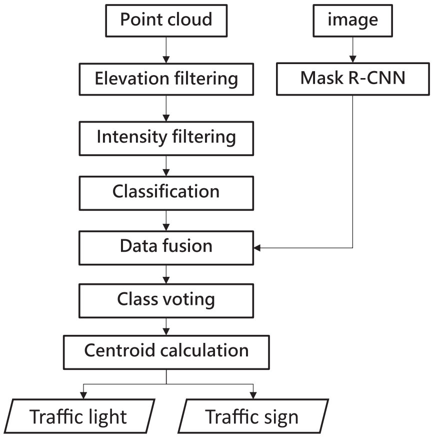
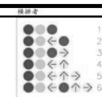


Fig. 10. Workflow of nonground feature identification.

conducive to improving the lateral control of an autonomous vehicle. Moreover, vehicular positioning performance in urban areas was notably improved by using the centerline map-matching algorithm [33], [34]. These cases highlight the importance of the centerline in HD maps. In general, centerline generation strategies can be divided into three groups: remote sensing images [35], trajectories [36], or extracted lane line points [37]. Although aerial or satellite image can cover a vast range and increase surveying efficiency, their accuracy is insufficient for the requirements of HD maps. In the trajectory-based method, the center points are generated directly based on the projected ground points along the trajectory. However, the accuracy of this generated centerline depends almost entirely on the quality of the trajectory. If the quality of the GNSS signal or the integrated INS/GNSS solution falls below expectations, the generated centerline is typically unsatisfactory. Generating the centerline by interpolating lane lines extracted from point cloud is not only accurate but also robust in various road scenarios. This method guarantees that the generated centerline is located within a lane. Following interpolation, the generated center points are also processed by modeling to obtain the final result.

2) Nonground Feature Generation: The aims of nonground feature generation are to identify traffic lights and certain traffic signs and convert these features into the HD map format [38]. The stepwise workflow is presented in Fig. 10. The procedure comprises point cloud processing and image recognition. In point cloud processing, ground features are first removed to optimize operational performance. Based on the observations, the intensity values of traffic lights are low, whereas the intensity value of traffic signs are high. Thus, these features can be conveniently extracted with intensity filtering. Although filtering out the ground point cloud suppress interference of traffic light and traffic sign extraction, it is impossible to completely eliminate noise points. Therefore, the statistical outlier removal filter, a function in the point cloud library (PCL) [39], is used to remove noisy points. In related work on traffic sign classification [40], the candidate point cloud of traffic signs was also extracted based on intensity. Traffic sign types are then determined by calculating the area after clustering these candidate points. Traffic signs can be categorized as circles, triangles, or rectangles. However, only using point cloud data easily results in misclassification because the point cloud is unorganized and its semantic information in insufficient. Therefore, we proposed classifying point cloud based on Euclidean distance and point number criteria before fusing the image recognition result.

TABLE VIII
TRAFFIC LIGHT PROPERTIES RECORDED IN HD MAPS [38]

Country code	Type	Figure	Color	Shape
V001	Traffic light (for vehicle)		red, Yellow, green	Circle
P001	Traffic light (for pedestrian)		red, green	rectangle

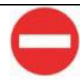
Extraordinary achievements in image processing have been made using deep learning. Object detection technologies, such as YOLO [41] and Mask-RCNN [42], are now mature. Mask-RCNN uses a pixel-level mask, known as RoIAlign, to locate a target and determine its corresponding attributes. To fuse the result of point cloud processing and image recognition, the classified point cloud is projected to the image processed by Mask-RCNN. If the point is consistent with an attribute, the point is retained; otherwise, the point is removed. However, the determined attribute may be incorrect; thus, a voting mechanism is used for a final determination of the attribute. Because the collected images are a series of connected images, the same point appears in various images, potentially causing misdetection. Hence, the number of assigned attributes for a certain point must be larger than a given threshold; otherwise, the point is removed. Moreover, the maximum number among the assigned attributes for a certain point is the final attribute of this point. Similarly, the category of an object is determined by calculating the maximum number of attributes of each point.

The HD map format standard records the properties of the traffic light and traffic signs, such as the coordinate of the centroid, type, country code, and shape (Tables VIII and IX). The relevant attribute can be recorded based on the recognized category. The coordinate of the centroid is recorded for each light or sign; computing the centroid of a traffic sign based on the point cloud is relatively straightforward. For traffic lights, the point cloud cluster with a particular attribute must be segmented into several lights. Principal component analysis is used to determine the vertexes of the bounding box of the traffic light. Then, the traffic light is segmented according to these vertexes. Finally, the centroids of each light can be computed.

F. Increasing the Scale of HD Maps

By establishing guidelines for operation and for the quality control of HD map format standards, the procedure of HD maps production can be standardized. The time and cost of HD map production also substantially decreased. These published guidelines and standards are adjusted using the roll planning method based on the experience and recommendations of experts in relevant fields. In addition to improving operations, HD map

TABLE IX
TRAFFIC SIGN PROPERTIES RECORDED IN HD MAPS [38]

Country code	Type	Figure	Shape	Color
W001	Turning right		Regular triangle	White background Red edge Black graph
O001	Stop		Octagon	Red background White edge White graph
P001	No entry		Circle	Red background White graph
R001	Vehicle weight limit		Circle	Red background Red edge Black graph
I001	Sightseeing area		Rectangle	Brown background White edge White graph
A001	Lane movement		Rectangle	Blue background White graph

verification is also necessary to improve map quality. Thus, we develop an automated HD map verification tool that not only accelerates the verification procedure but also reduces human error because of weariness or a momentary oversight. This focus of verification tool is the assessment of attributes, which are standardized but cumbersome for humans. For example, the tool verifies the ID of the predecessor and successor links, the code for corresponding features, and whether an attribute is incorrectly filled or omitted. Our tool also contains the functionality to evaluate the attribute of road marking, parking lot, object, waypoint, pole, traffic sign, and traffic light. Due to these improvements, various regions of Taiwan are now covered by HD maps, and this area continues to expand.

III. RESULTS AND DISCUSSION

This section elaborates on the key achievements of our HD maps projects. The results are divided into various subcategories.

A. Publication of HD Maps Guidelines and Standards

To verify the integrity and reliability of the proposed guidelines and standards, they must be reviewed by credible industry organizations. Taiwan Association of Information and Communication Standards (TAICS) is an industry organization in Taiwan with the objective of promoting the implementation of domestic industry standards to expand regional influence and bridge local industry and global standards. The proposed guidelines and standards were reviewed through the formal procedure of TAICS and were optimized by incorporating suggestions from experts and scholars. Various publication milestones for HD map technical documents are listed in Table X.

The OpenDRIVE format standard was updated from version 1.5 to version 1.6; thus, the published HD maps data content and format standards was updated to version 1.1 also needs to keep pace with the times to incorporate the changes. In addition to the "Operation and verification guidelines for HD Maps updating – Permanent static data," the format standard for dynamic HD maps is also ready for publication.

TABLE X
PUBLICATION MILESTONES FOR HD MAP TECHNICAL DOCUMENTS

Technical documents	Time	Activities
HD maps operation guidelines v1	2018.12.26	Published @ TAICS
HD maps operation guidelines v2	2019.10.17	Published @ TAICS
Verification and validation guideline for HD maps	2020.06.05	Published @ TAICS
HD maps data content and format standards v1.1	2020.03.16	Published @ TAICS
Operation and verification guidelines for HD maps updating – permanent static data	2021.10.21	Published @ TAICS

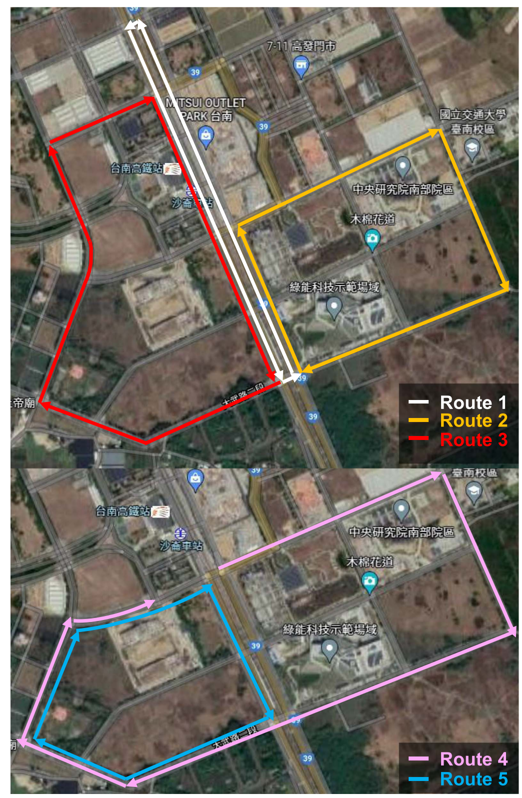


Fig. 11. Routes for data acquisition in the test field.

B. Dynamic Updating of HD Maps

Data acquisition with certified third-party platforms was performed at five routes in the research park around Academia Sinica in southern Taiwan, at Taiwan CAR Lab, and on campus, shown in Fig. 11. The categories of changed physical features are presented in Table XI. We used four third-party platforms equipped with similar sensors to tour the test routes several times to simulate data crowdsourcing. The driving route times of each vehicle are listed in Table XII.

TABLE XI
CATEGORIES OF CHANGES OF PHYSICAL FEATURES

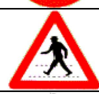
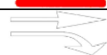
Category	Figure	Note
Traffic light (for vehicle)		Horizontal and circular traffic lights
Traffic light (for pedestrian)		Vertical and square traffic lights for pedestrian
Restrict traffic sign		Circle traffic signs with red edge
Limit traffic sign		Circle traffic signs with red edge and slash
Warning traffic sign		Triangle traffic signs with red edge
Arrow		White arrows on the lane
Lane line (dashed line)		White and yellow dashed lines
Text (for speed)		Speed limit text on the lane

TABLE XII
DRIVING ROUTE TIMES FOR EACH VEHICLE

	Driving route and corresponding times (times)				
Platform	**Route 1**	**Route 2**	**Route 3**	**Route 4**	**Route 5**
Vehicle1	**3**	**3**	**3**	**–**	**–**
Vehicle2	**3**	**3**	**3**	**–**	**–**
Vehicle3	**–**	**–**	**–**	**3**	**–**
Vehicle4	**2**	**3**	**–**	**–**	**2**

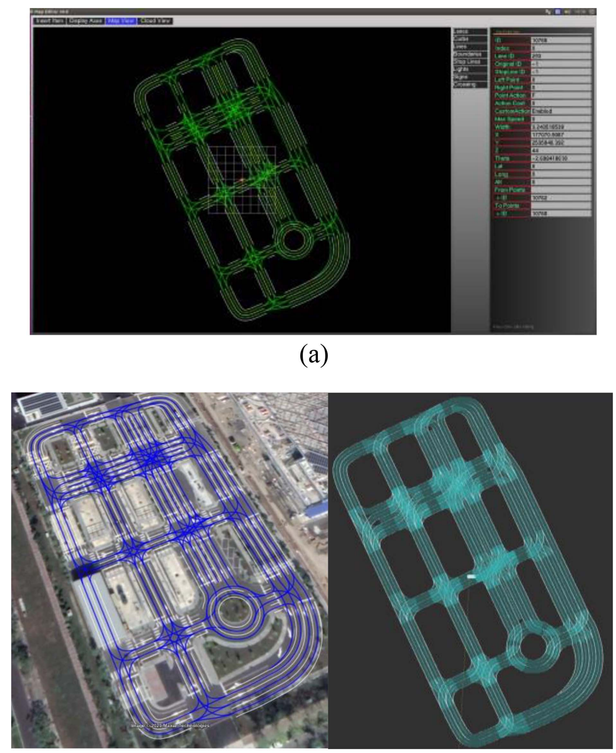
TABLE XIII
RESULT OF INSERTION CHANGE DETECTION

	True inserted changing	Commission	Omission	Precision	Recall
Traffic light (for vehicle)	6	3	0	66.7%	100%
Traffic light (for pedestrian)	0	16	0	0.0%	N/A
Restrict traffic sign	3	4	0	42.9%	100%
Limit traffic sign	0	3	0	0.0%	N/A
Warning traffic sign	1	0	0	100%	100%
Arrow	23	10	0	69.7%	100%
Lane line (dashed line)	3	1	0	75.0%	100%
Text (for speed)	55	57	3	49.1%	94.8%
Total				50.4%	99.1%

Tables XIII and XIV present the performance for detection of changed features. Because commission errors are substantially more common than omission errors, the precision was low at approximately 50.4% for insertions. However, the average recall reached 99.1% and 100%, indicating that most change events could be detected by third-party platforms to update HD maps

TABLE XIV
RESULT OF REMOVAL CHANGE DETECTION

	True removed changing	Commission	Omission	Precision	Recall
Traffic light (for vehicle)	0	4	0	0.0%	N/A
Traffic light (for pedestrian)	0	11	0	0.0%	N/A
Restrict traffic sign	0	1	0	0.0%	N/A
Limit traffic sign	0	1	0	0.0%	N/A
Warning traffic sign	0	1	0	0.0%	N/A
Arrow	4	4	0	50.0%	100%
Lane line (dashed line)	6	3	0	66.7%	100%
Text (for speed)	14	14	0	50.0%	100%
Total				20.8%	100%



(a)

(b) (c)

Fig. 12. Illustration of OpenDRIVE map and converted map in Taiwan CAR Lab. (a) Original OpenDRIVE maps. (b) Google Earth maps. (c) Lanelet2 maps.

and to ensure road safety. The correctness of the updated HD maps was verified with the certified verification procedure.

C. Automated HD Map Format Conversion Tool

The format conversion tool provides a clear and straightforward user interface. Its performance for conversion was evaluated with various OpenDRIVE maps in Taiwan CAR Lab (details are illustrated in Section III-D.), areas generated by various professional surveying companies. Fig. 12(a) displays the original OpenDRIVE maps in the ASSURE map tool. The OpenDRIVE map can be easily be converted to Google Earth

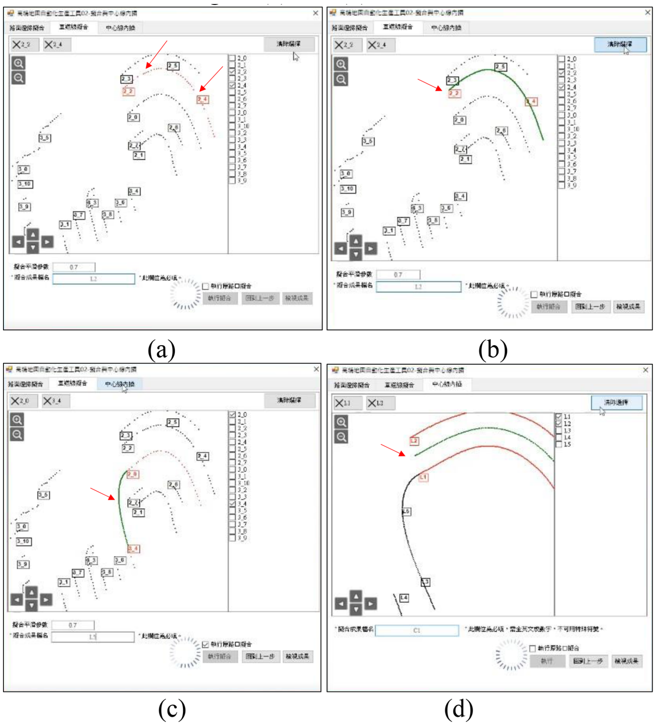


Fig. 13. Lane modeling. (a) Lane line selection. (b) Results for each lane line. (c) Transition line modeling. (d) Centerline interpolation.

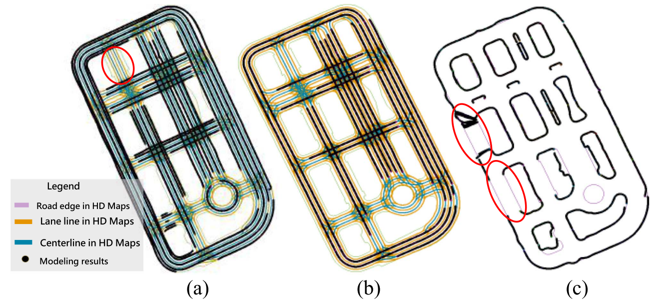


Fig. 14. Taiwan CAR Lab modeling. (a) Lane line modeling. (b) Centerline modeling. (c) Road edge modeling.

TABLE XV
GROUND FEATURE GENERATION ACCURACY

	Lane line	Centerline	Road edge
Mean	0.116 m	0.078 m	0.455 m
RMSE	0.203 m	0.110 m	0.744 m
Max error	1.196 m	0.866 m	3.095 m

map (.xml) or Lanelet2 (.osm) maps, as displayed in Fig. 12(b) and (c). Because the OpenDRIVE maps were generated based on the OpenDRIVE v1.5 format, localized traffic signs, or traffic lights were defined in the userdata in OpenDRIVE. Therefore, the ASSURE maps tool could not show all of its features in the interface because the ASSURE map tool supports OpenDRIVE v1.6. Thus, only the correctness of the relationship between lanes and roads was analyzed. All junctions, road geometries, and connections between lanes were transformed properly. The usability and accurately of the automated HD map format conversion tool will be reinvestigated after the HD map format standard is updated to OpenDRIVE v1.6. The tool will be revised if any conversion is incorrect.

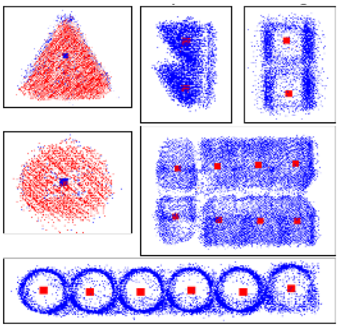
D. Semiautomated HD Map Production Tool

The semiautomated HD map production tool generated both ground and nonground features. The data path and parameters required in the algorithm can be provided by users to customize data processing in both interfaces. A window for visualizing the ground feature generation function is also provided for users to monitor the results. The user can select lanes for modeling based on their prior knowledge as presented in Fig. 13(a) and (b). If the modeling result does not meet expectations, the modeling can be redone to achieve a better result. Moreover, the transition line and centerline can also be generated by the user, as shown in Fig. 13(c) and (d).

The Taiwan CAR Lab was chosen as the test field for evaluating the performance of the algorithms in the tool. Taiwan CAR Lab is the first test field constructed in Taiwan for research on autonomous vehicles. The test field includes various roads with common road scenarios in Taiwan, such as roundabouts, road merges, curved roads, tunnels, and railroad crossings. It is a suitable simulation environment for assessing the stability of the proposed algorithm.

The results of mapping at Taiwan CAR Lab were compared against verified HD maps based on the standard verification procedure. The ground feature generation at Taiwan CAR Lab is illustrated in Fig. 14, and the accuracy of the modeling results relative to verified HD maps is detailed in Table XV. Most modeled lane lines, centerlines, and road edges were identical to those in the verified HD maps. The accuracy of lane lines and centerlines was also less than 30 cm vertically, meeting the accuracy requirement for HD maps. However, some modeled lane lines were broken, such as the marked areas in Fig. 14, because the road markings were too complex for clear lane lines to be extracted. Consequently, centerlines were affected because they are interpolated based on lane lines. Although the overall geometry of the road edges was consistent with the verified HD maps, road edges had more modeling errors than lane lines did. The location of the road edge is more difficult to identify than the location of lane lines due to the effects of weeds and soil around the road edge. The areas marked in Fig. 14(c) were paved with a particular pavement that was constructed using metal cladding because such pavements are highly reflective, it led to the misidentification of road markings and the road surface during intensity filtering.

For nonground feature generation, the centroids of the traffic lights and traffic signs were calculated from the point cloud and their attributes were recorded (Fig. 15). The accuracy was evaluated by computing the distance of between the coordinates of the extracted centroids and the centroids from the verified HD map (Table XVI). Fig. 16 presents visualizations of the error for traffic lights and signs; only 10 points had errors greater than 20 cm in 3-D space. Therefore, the results are of sufficient accuracy when compared against HD maps.



(a)

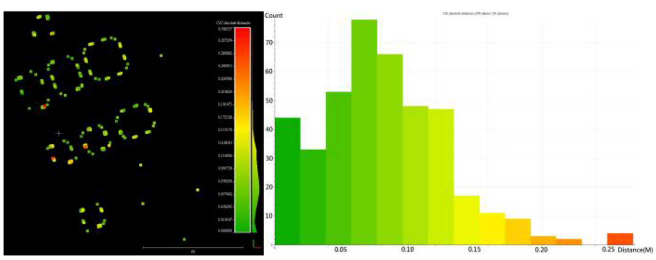
type	X	Y	Z
traffic light 0	177007.9	2535894	50.255
traffic light 1	177007.7	2535894	50.23
traffic light 2	177007.6	2535895	50.215
traffic light 3	177007.4	2535895	50.195
traffic light 4	177007.3	2535895	50.175
traffic light 5	177007.4	2535894	50.245
traffic light 6	177007.2	2535894	50.22
traffic light 7	177007	2535894	50.21
traffic light 8	177006.9	2535895	50.195
traffic light 9	177006.8	2535895	50.18
traffic light 10	177016	2535904	50.135
traffic light 11	177015.9	2535905	50.11
traffic light 12	177015.7	2535905	50.14
traffic light 13	177015.6	2535905	50.145
traffic light 14	177015.6	2535904	50.115
traffic light 15	177015.4	2535904	50.12

(b)

Fig. 15. Extracted centroids. (a) Centroids of traffic lights and traffic signs. (b) Attributes of the extracted features [31].

TABLE XVI
ACCURACY OF NONGROUND FEATURE GENERATION [38]

	Mean	**RMSE**	**Max error**	**Min error**
Distance	0.088 m	0.044 m	0.266 m	0.009 m



(a) **(b)**

Fig. 16. Error distribution for traffic lights and signs. (a) Location of traffic lights and signs with errors. (b) Error distribution [38].

A confusion matrix is often used to evaluate the classification performance in AI applications. We used a confusion matrix to quantify the classification results for traffic lights and signs. Data on the traffic lights and signs in Taiwan CAR Lab include data on traffic restrictions, on warnings, and on traffic lights for both vehicles and pedestrians, and the classification evaluation included these features. The precision, recall, and F1-score were the three main indexes used for evaluation. They are calculated as follows:

$$\text{precision} = \frac{\text{True Positive (TP)}}{\text{True Positive} + \text{False Positive (FP)}} \tag{1}$$

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative (FN)}} \tag{2}$$

$$F1 - \text{score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}. \tag{3}$$

Table XVII presents the results of the confusion matrix for classification. Only one false positive event occurred due to inaccurate point cloud segmentation of the traffic lights. The other traffic lights and traffic signs were correctly identified based on our algorithm.

TABLE XVII
PERFORMANCE OF CLASSIFICATION OF TRAFFIC LIGHTS AND SIGNS [38]

Type	**TP**	**FP**	**FN**	**Precision**	**Recall**	**F1-score**
Traffic light (for vehicle)	1	0	0	100%	100%	100%
Traffic light (for pedestrian)	4	0	0	100%	100%	100%
Restrict traffic sign	280	1	0	99.644%	100%	99.821%
Warning traffic sign	92	0	0	100%	100%	100%
total	377	1	0	99.733%	100%	99.866%

TABLE XVIII
COST OF HD MAP PRODUCTION PER KILOMETER

Year	**Cost (New Taiwan dollars/km)**	**Produced HD maps**
2018	1 200 000	Point cloud map, shapefile
2019	1 000 000	Point cloud map, shapefile
2020	350 000	Point cloud map, shapefile, OpenDRIVE map
2021	350 000	Point cloud map, shapefile, OpenDRIVE map

E. Scale of HD Map Production in Taiwan

Table XVIII presents the cost of HD map production per kilometer in NTD/km in recent years. With the accumulation of practical experience and the improvement of HD map surveying and production, the cost has dramatically decreased from 1 000 000 NTD/km in 2018 and 2019 to 350 000 NTD/km in 2020 and 2021. Furthermore, the contents of the HD maps have also expanded from point cloud maps and shapefile data to OpenDRIVE maps. The time cost of HD map production and verification is rapidly declining every year. The time cost for vector maps decreased from 6.7 days/km in 2019 to 2.2 days/km in 2020. The time cost for the OpenDRIVE map decreased from 16.9 days/km in 2019 to 7.7 days/km in 2020. On the other hand, the total time cost for verification decreased from 93 days in 2019 to 85 days in 2020. There are 11 produced HD maps over Taiwanese regions, and the total mileage is approximately 102.98 km.

IV. CONCLUSION

With advances in autonomous driving technologies and the evolution of the automotive industry, autonomous vehicles will become a reality. HD maps are a key component in autonomous vehicle development. To apply HD maps, the challenges of popularizing these maps must be overcome by both reducing the cost of producing these maps production but also by advocating for national policies supporting the development of HD maps in the future. Therefore, we proposed several strategies to overcome these difficulties with the support of the MOI and academic institutions. We published HD map guidelines and standards, established procedures for producing HD maps, and developed an HD map format conversion tool and a semiautomated HD map production tool. Recent explorations in HD maps reveal that these strategies have been influential in increasing the performance and progress of HD maps in Taiwan. The production capacity of professional surveying companies in Taiwan has also been recognized. By laying the groundwork for HD maps, related autonomous driving techniques can naturally complement each other to rapidly fulfill the vision of autonomous vehicles.

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