Mapping in the Future: Advancing HD Maps Creation with Semi-Automated Feature Extraction

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ABSTRACT:

The production of high-definition maps (HD Maps) is a multi-stage, resource-intensive process that demands substantial investments in specialized equipment, skilled labor, and time. This study introduces a semi-automated mapping tool aimed at addressing these challenges through the integration of point cloud data, trajectory information, and image-based AI algorithms. One of the key innovations of this tool is a user-friendly graphical user interface (GUI), which enhances usability by facilitating data import, preprocessing customization, and feature visualization. The tool focuses on extracting essential road features such as lane lines, stop lines, directional arrows, and traffic signals, outputting data in various formats including LAS, PCD, and SHP. Performance evaluations were conducted in both controlled and real-world environments. In the Taiwan CARLab, the tool demonstrated high accuracy under diverse traffic scenarios. Testing on Taiwan's National Highway No. 1 further confirmed the tool's robustness in handling real-world conditions, achieving up to a 50–70% reduction in processing time compared to manual digitization. These findings highlight the tool's potential to significantly reduce production costs while maintaining accuracy, thereby facilitating wider adoption of HD Maps in autonomous driving applications.

1. INTRODUCTION

The production of high-definition maps (HD Maps) involves multiple stages that require significant investments in equipment, labor, and time. Data collection necessitates specialized hardware such as LiDAR sensors, GPS receivers, and high-resolution cameras, which can be costly to acquire and maintain (Chiang et al., 2022). Manual data processing, particularly for feature digitization, is labor-intensive and time-consuming (Sester et al., 2017). Skilled personnel are required to analyze and manage data, further increasing labor costs.

This study presents a semi-automated tool developed to produce HD Maps. The primary objective of this tool is to replace labor-intensive manual digitization with a more efficient semi-automated process, thereby reducing the substantial labor costs associated with HD Maps production (Van Nieuwenhuizen & Hegeman, 2020). Additionally, the tool integrates a user-friendly graphical user interface (GUI) to streamline operations. This GUI enables users to easily import data, configure preprocessing options, monitor output logs, and visualize extracted features in real-time. By providing an accessible interface, the tool bridges the gap between research and practical application, making HD Maps mapping technologies available to a broader range of users.

The tool focuses on extracting essential road surface features from point cloud data, including lane lines (solid and dashed), zebra crossings, directional arrows, stop lines, and lane centerlines, which are subsequently modeled into shapefile vector formats. To achieve this, multiple data sources are utilized, enhancing the robustness and accuracy of feature extraction.

The importance of automation in HD map production has been widely recognized in the literature. Lots of studies have emphasized the need for AI-based feature extraction to improve efficiency in transportation infrastructure projects. Automated tools that integrate point cloud and image data have shown significant promise in reducing manual workload and enhancing accuracy. Chang (2023) demonstrated the use of a cloth simulation filter (CSF) and Otsu's thresholding method to separate ground points and extract road markings, such as stop lines and lane lines, from Mobile Laser Scanning point clouds. Additionally, Ma et al. (2019) proposed a robust approach for extracting lane features from curved roads, which highlights the adaptability of automated methods in diverse road environments. These tools are crucial for enabling scalable map production for autonomous vehicle navigation, where high levels of spatial precision and data integration are required.

1.1 Data Sources

This study uses three primary data sources: point cloud data, trajectory information, and images, all collected using RIEGL instruments. Point cloud data provides a high-precision spatial representation of road surfaces and surrounding objects. It is acquired using LiDAR sensors, which are known for their accuracy in capturing complex surface geometries. Trajectory data, recorded through integrated INS and GNSS systems, ensures precise positioning and alignment of point cloud frames, which is essential for maintaining data consistency across large areas. Additionally, high-resolution image data complements the point cloud by providing visual context for identifying road features, including traffic signals and lane markings. AI models, such as Mask R-CNN, leverage these images to automate the detection of complex features.

1.2 Feature Extraction

The semi-automated tool employs a combination of geometric analysis and AI-driven feature recognition to extract key elements from the data. Point cloud clustering algorithms segment surface features, such as lane markings, based on reflectivity and spatial distribution. Meanwhile, image-based models detect and classify visual features like signals. The trajectory data is helpful for feature extraction.

The role of AI in feature extraction has been explored extensively. Van Nieuwenhuizen and Hegeman (2020) highlighted the advantages of deep learning models in reducing the error rates associated with manual digitization. Similarly, recent advancements in oriented bounding box (OBB) classification have demonstrated improvements in the identification and modeling of road features from clustered point data.

1.3 User Interface and Testing

The graphical user interface (GUI) was designed to provide an intuitive and accessible platform for users, aligning with the goal of practical applicability beyond academic research. The GUI includes modules for data import, preprocessing configuration, real-time output logging, and visual display of extracted features. Usability studies have shown that well-designed interfaces can significantly reduce the time required for data management and verification.

Testing was conducted in both controlled and real-world environments to evaluate the tool's robustness. The CARLab in Taiwan served as a closed test field, providing a controlled setting for algorithm testing. This facility includes various traffic scenarios, such as curved roads, tunnel, and intersections, which are critical for testing feature detection capabilities. For real-world assessment, a one-kilometer section of Taiwan's National Highway No. 1 was selected due to its repetitive and structured features. The highway tests demonstrated the tool's effectiveness in replacing manual digitization with semi-automated processes, achieving high accuracy rates across multiple feature types.

The findings from this research contribute to ongoing efforts to enhance HD map production workflows. By integrating AI and automated data processing techniques, this study addresses key challenges in scalability and cost reduction, making HD maps more accessible for autonomous driving applications.

2. METHODOLOGY

The methodology for this research follows a structured data processing pipeline designed to efficiently extract essential road features by combining multiple data sources, including point cloud data, trajectory information, and images. This comprehensive workflow, illustrated in Figure 1, is divided into multiple stages—data preprocessing, filtering, feature extraction, and final output generation. Each stage plays a crucial role in ensuring both the accuracy and scalability of HD Maps production.

The process begins with point cloud data preprocessing, which undergoes initial filtering using the Cloth Simulation Filter (CSF). This method separates ground and non-ground points by simulating the behavior of a falling cloth over inverted point clouds, helping to isolate the point clouds of road surface. Once ground points are identified, further processing such as voxel downsampling and noise filtering is applied to optimize data density while retaining essential features. Curb detection and high-reflectivity point extraction are then performed to define lane boundaries and identify painted road markings.

Simultaneously, image data collected from onboard cameras is processed using AI models like Mask R-CNN. This step involves detecting critical road features, such as traffic signals, and generating bounding boxes around them. These image-based features are aligned with the point cloud data, ensuring spatial consistency across both data types. Trajectory data captured from integrated GNSS and INS systems is used to maintain accurate georeferencing and assist extraction throughout the process.

In the feature extraction phase, point cloud clustering is applied to segment road elements, with Euclidean distance-based clustering followed by Oriented Bounding Box (OBB) classification. OBB is preferred over Axis-Aligned Bounding Box (AABB) due to its ability to accommodate object orientations that do not align with the coordinate axes, thereby providing more precise feature representation (Gottschalk et al., 2000; Jiang, 2017). The classification process identifies various road markings, including lane lines, stop lines, and directional arrows, based on their geometric properties.

After feature extraction, the data is exported in multiple formats to support various applications. LAS files enable to store the full-resolution point cloud data, PCD files offer compatibility with 3D visualization tools, and shapefiles store vector-based features for integration into Geographic Information System (GIS) software. The final output undergoes manual verification to confirm feature accuracy and attribute completeness, ensuring reliability for HD Maps used in autonomous driving and other advanced mapping systems.

This multi-stage methodology enables robust, high-precision feature extraction while reducing the manual workload traditionally associated with HD Maps production. By integrating automation and cross-referencing multiple data sources, the workflow improves both efficiency and scalability, positioning it as a practical solution for large-scale, real-world mapping projects.

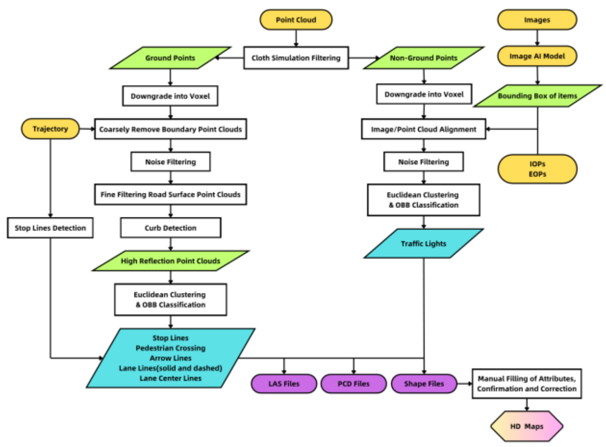

Figure 1. Flowchart of semi-automated HD Maps feature extraction.

2.1 Data Acquisition

Data for this research was gathered using the RIEGL VMX-250 system, as shown in Figure 2, which captures both high-precision point cloud and image data. Trajectory data was simultaneously recorded using GNSS and INS to provide precise georeferencing for each data frame.

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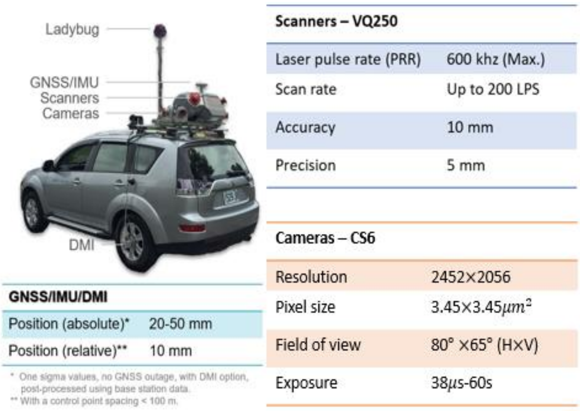

Figure 2. RIEGL VMX-250 system (Zeng, 2020).

2.2 Data Preprocessing

The raw point cloud data undergoes several preprocessing steps to ensure the accuracy and efficiency of feature extraction. Ground points are separated using the Cloth Simulation Filter (CSF) method (Zhang et al., 2016), which provides a reliable approach to isolate road surfaces from point cloud data. Unlike traditional filtering methods that rely on elevation and slope, which struggle in complex or steep terrains, the CSF technique models a falling cloth over inverted point clouds to create a reference surface, as shown in Figure 3. To optimize computational performance, the point cloud is then voxelized, reducing data density while preserving essential details.

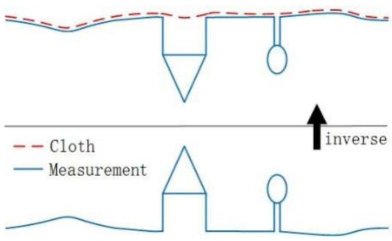

Figure 3. Cloth simulation filter (Zhang et al., 2016).

Several key parameters influence the outcome of the CSF simulation, including rigidity, cloth grid resolution, and the classification threshold. Rigidity determines how closely the cloth conforms to the ground surface, with this study selecting a 'flat' setting due to the relatively even terrain in the test area. The cloth grid resolution, set to 0.1 meters, defines the density of cloth nodes, while the classification threshold, also set to 0.1 meters, specifies the maximum elevation difference allowed between the point cloud and the simulated reference surface. The implementation of CSF was carried out using CloudCompareStereo, which offers an efficient and user-friendly platform for point cloud processing, enhancing its suitability for diverse scenarios.

Additional preprocessing involves noise filtering to remove outliers and irrelevant data points. Curb detection is performed to define lane boundaries, and high-reflectivity points, indicative of painted road markings (Li et al., 2019), are extracted for further analysis.

2.3 Feature Extraction

Feature extraction combines geometric analysis with AI-based methods. High-reflectivity points undergo clustering using Euclidean distance, and the resulting clusters are analyzed through oriented bounding box (OBB) classification. The classification of different road surface markings on the pavement relies on the geometric characteristics of each point cloud cluster obtained through clustering. In this study, the algorithm parameters were refined to align with road marking design standards, facilitating accurate recognition of various marking types. To deduce the geometric properties of each cluster, minimum bounding boxes were created to encompass all points within each cluster, allowing for the calculation of their length and width. This approach proved advantageous due to its regular structure and computational efficiency, making bounding boxes effective for object representation. OBB is preferred over axis-aligned bounding box (AABB) as it offers greater flexibility in accommodating the varying orientations of road features, such as directional arrows, which may not align perfectly with the coordinate axes, as shown in Figure 4. Literature, including studies by Ma et al. (2019), has shown that OBB improves the accuracy of feature boundary fitting in complex environments.

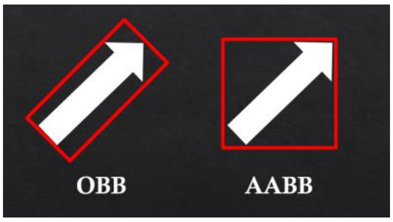

Figure 4. Oriented bounding box and axis-aligned bounding box (Chang, 2023).

Image data is processed using an AI model, specifically Mask R-CNN, to detect and outline key objects by generating bounding boxes around them. These detected features, such as traffic signals, are then aligned with point cloud data to achieve precise spatial integration, as shown in Figure 5. The process begins with the AI model identifying important objects in the image data, including bounding box coordinates that serve as spatial markers. Once the bounding boxes are applied, the corresponding point cloud data within these regions is extracted for further analysis. This step ensures that both image and spatial data are synchronized, which enhances detection accuracy by leveraging the strengths of each data type. Point cloud data, known for its spatial precision, captures structural details, while images provide contextual and visual information. The workflow progresses with noise removal to isolate relevant features such as signal posts or traffic signs. Noise filtering reduces false positives and ensures that only the significant point cloud clusters remain. Afterward, the algorithm calculates the centroids of the extracted features, providing a precise spatial reference for each object. These refined data points are then exported as shapefiles, enabling seamless integration with Geographic Information System (GIS) applications. This combined approach significantly improves the robustness of feature extraction by utilizing both geometric and visual data sources. The AI-assisted methodology minimizes manual effort, increases processing efficiency, and reduces the likelihood of errors associated with independent data processing methods. This synergy between image and point cloud data makes the tool suitable for scalable, high-precision mapping projects in autonomous driving applications.

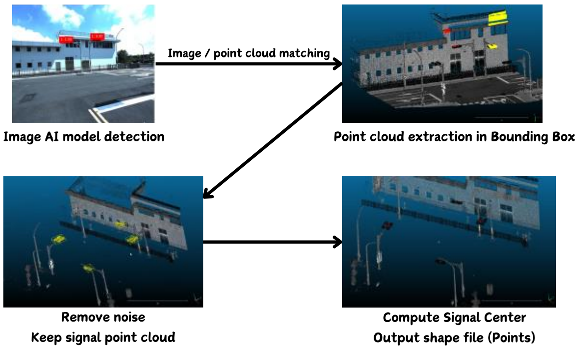

Figure 5. Image AI model-assisted detection process.

Figure 6. Taiwan CARLab (CARTURE, 2019).

2.4 Data Output

The extracted features are exported in multiple formats to support various applications. LAS files contain the full-resolution point cloud data, while PCD files provide compatibility with 3D visualization tools. Shapefiles store vector-based features for use in GIS software. The final output is subjected to a manual verification process to confirm feature accuracy and attribute completeness, ensuring the reliability of the HD Maps.

To ensure the reliability of these exported outputs, a manual verification process is implemented. This step involves cross-referencing the extracted features against the original data to confirm both spatial accuracy and attribute completeness.

3. RESULTS AND DISCUSSION

3.1 Experiment Setups

This study evaluated the performance of the semi-automated HD Maps production tool in two distinct environments: the closed test field at Taiwan CARLab and a one-kilometer segment of Taiwan National Highway No. 1. These environments were selected to provide both controlled and real-world scenarios, offering a comprehensive assessment of the tool's accuracy, efficiency, and practicality.

(1) Controlled Test Field:

The Taiwan CARLab, located in Shalun, Tainan, is a specialized closed-field testing site designed for autonomous driving research as shown in Figure 6. For this study, data acquisition was conducted using the RIEGL VMX-250 system, supplied by a professional surveying firm. The CARLab features thirteen simulated traffic scenarios, including railway crossings, curved roads, and tunnels, which provide a diverse and controlled environment to test and calibrate algorithms. This controlled environment was chosen for its well-defined conditions, including clearly marked road features and the absence of external vehicle interference. These characteristics enhance the accuracy and reliability of the experiments.

(2) Real-World Test Field:

The second test environment was a one-kilometer segment of Taiwan National Highway No. 1. This highway section was chosen due to its repetitive features, which are common in real-world road networks. These features, such as dashed lane lines, solid lane lines, and lane centerlines, provide an ideal scenario to demonstrate the tool's ability to automate feature extraction efficiently and accurately.

3.2 Graphical User Interface

Figure 7. User interface of semi-automated HD Maps production tool.

The development of a graphical user interface (GUI) was a crucial aspect of this research, aimed at ensuring practical usability beyond academic exploration. The GUI was designed to facilitate user interaction with the mapping tool, making the system accessible to both technical and non-technical users. It includes several key components, each serving a specific function within the workflow.

The interface shown in Figure 7, the **Import Data** section allows users to easily import point cloud and image data files and so on into the execution system. Once the data is imported, the

Preprocessing Options panel enables users to configure parameters such as voxelization (downsampling), ground point filtering, and noise reduction. This customization ensures that the system can adapt to various data qualities and project requirements.

Users can select the desired **Output Format**, choosing between LAS, PCD, and shapefile formats, depending on their needs. The **Available Layers in the Field** panel is designed to help users preemptively evaluate whether the input data includes critical features such as stop lines, directional arrows, and zebra crossings. This pre-assessment allows users to configure the system more effectively, thereby accelerating algorithm performance and enhancing feature extraction accuracy. An **Output Log Messages** window provides real-time updates on the processing status, informing users of any errors or completed tasks. Finally, the **Canvas for Display** serves as a visualization area that displays point cloud data and extracted features for inspection, without extensive interactive functionality.

These features collectively streamline the map production process, allowing users to efficiently manage data, monitor progress, and export results. By integrating an intuitive interface, the system bridges the gap between academic research and real-world application, empowering a wider range of users to benefit from high-precision mapping technologies.

3.3 Road Surface Marking Extraction

The extraction of road surface markings is another significant achievement of this research. The process starts by isolating ground points from the point cloud data using the cloth simulation filter (CSF). This separation enables the subsequent focus on surface details without interference from non-ground elements. Once the ground points are isolated, a binarization technique based on Otsu's thresholding method is applied to distinguish between paint markings and asphalt surfaces in the point cloud. This step ensures that the high-reflectivity paint areas, such as lane markings and stop lines, are clearly segmented. The results of Otsu's thresholding method are illustrated in Figure 8, which demonstrates the clear segmentation of painted and asphalt surfaces.

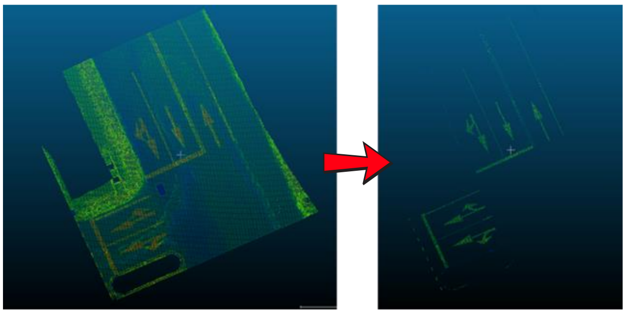

Figure 8. Binarization of road surface markings.

The extraction process is further refined using trajectory data to assist in accurately identifying stop lines. Following this, the segmented points are grouped into clusters through a point clustering algorithm. Each cluster is analyzed to determine its geometric properties using oriented bounding box (OBB) analysis, which calculates the length and width of the cluster. Based on these geometric characteristics, the clusters are classified into various road objects, including zebra crossings, directional arrows, solid and dashed lane lines, and lane centerlines.

A visual representation of the extracted road surface markings is shown in Figure 9. The red lines indicate the extracted stop lines, while the cyan lines represent the zebra crossings. Directional arrows are highlighted in green, with yellow lines marking double-lane lines. Single-lane lines are shown in white, and purple lines indicate the lane centerlines. This visualization confirms the effectiveness of the extraction and classification methods applied.

This classification process allows for efficient and accurate modeling of road surface markings, contributing to the overall accuracy of the HD Maps. The output data is stored in formats suitable for further analysis and integration into mapping applications, ensuring compatibility with industry-standard tools. Testing demonstrated that this method effectively handles various road marking types, making it a robust solution for large-scale mapping projects.

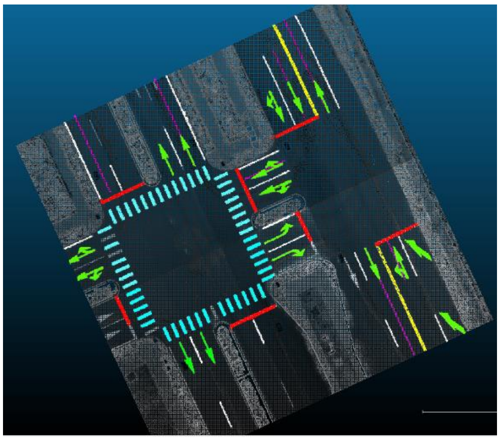

Figure 9. Extraction results of closed test field.

Additionally, one of the research’s objectives focused on highways, given their relatively simple and repetitive features. Such characteristics make highways ideal candidates for semi-automated extraction to replace manual digitization. To validate this approach, a one-kilometer section of Taiwan's National Highway No. 1 was selected for testing. During the highway tests, the tool maintained high performance despite the dynamic and less controlled environment. The results are shown in Figure 10, where white lines represent dashed lane markings, yellow lines indicate solid lane lines, and purple lines denote the lane centerline. These results illustrate the tool's ability to efficiently extract and classify highway features, further supporting its scalability for large-scale applications.

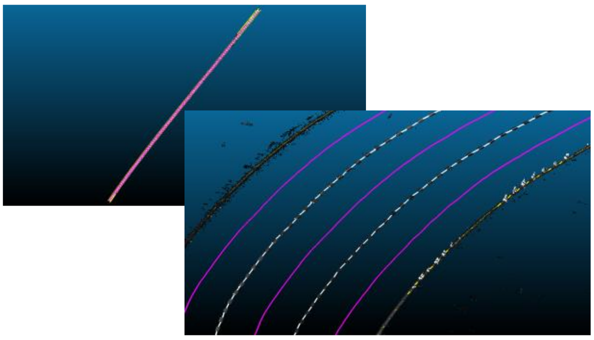

Figure 10. Extraction results of Taiwan's National Highway No. 1.

3.4 Traffic Signal Extraction

The extraction of traffic signals was a key component of this study. The process began by separating non-ground points from the point cloud data using a cloth simulation filter (CSF). An AI model was then applied to the image data to detect traffic signals, generating bounding boxes around identified objects. These bounding boxes were spatially aligned with the point cloud data, allowing for the extraction of point cloud data corresponding to each detected signal. Points within the bounding boxes were further refined to isolate and filter traffic signal points, and the centroid of each signal was calculated. The final output was saved in shapefile format for use in HD maps.

Testing in the controlled environment at Taiwan CARLab revealed that out of 59 traffic signals present, the system successfully extracted 50, with 9 signals missed. No false positives were detected during the extraction process. The primary reason for missed detections was the limited field of view of the cameras, which were mounted on the sides and rear of the vehicle, causing some signals to be excluded from image capture. Despite these limitations, the results demonstrated strong potential for automated traffic signal extraction.

The performance results for traffic signal extraction are summarized in Table 1 and the display results of signal extraction are shown in Figure 11 below. The red dot in the figure is the center position of the extracted signals.

Table 1. Accuracy analysis of extraction results of lane lines

Test Environment	Taiwan CARLab
Total Signals	59
Extracted Signals	50
Missed Signals	9
False Positives	0
Accuracy Rate	84.7%

These results highlight the effectiveness of combining point cloud data and image-based AI for traffic signal detection while also indicating areas for further optimization in sensor placement and coverage.

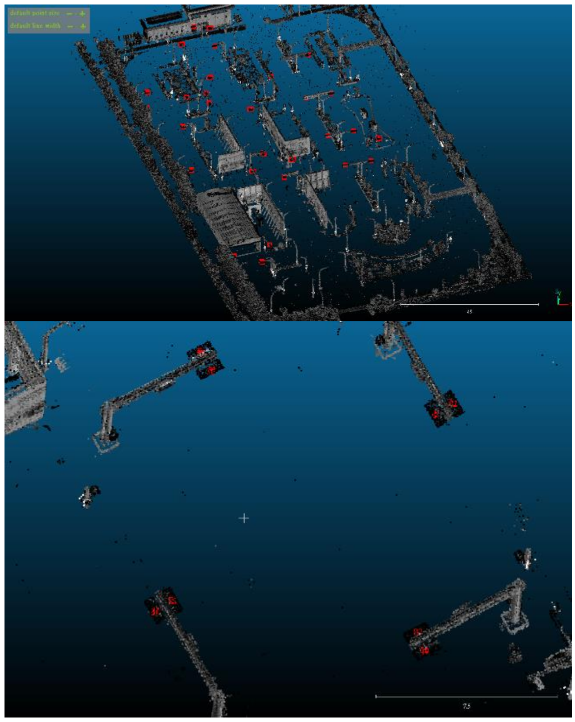

Figure 11. Result of signal extraction.

3.5 Quantitative Analysis

The comparative analysis of manual digitization and the semi-automated tool, based on a one-kilometer segment of the real-world test field: Taiwan National Highway No. 1, demonstrates a significant improvement in production efficiency for HD map generation. As shown in Table 2, the semi-automated tool requires only 40 minutes to complete the entire process, compared to 90–120 minutes for manual digitization. This represents a reduction in processing time by approximately 50–70%, highlighting the tool's ability to dramatically decrease production costs while maintaining accuracy. These results validate the tool's potential as a cost-effective solution for HD map production, facilitating broader adoption in autonomous driving applications.

Table 2. Comparison of processing time between manual digitization and semi-automated tool for HD Maps production

Process	Manual Digitization (min)	Semi-Automated Tool (min)
Downsample	90~120	7
Outlier Removal		3
Ground Extraction		7
Curb Detection		4
High-Intensity Point Cloud Extraction		3
Marking Extraction		1
Manual Review and Fine-tuning		20
Total Duration	90~120 min	45 min

These findings reinforce the importance of automation in large-scale mapping projects and emphasize the tool's role in enhancing both productivity and cost-efficiency.

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