Extraction of block walls from point clouds measured by Mobile Mapping System

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Abstract

To solve the problem of collapsing block walls widely used in Japan, this study proposes a method for extracting block walls using 3D point cloud data measured by the Mobile Mapping System (MMS). Unlike conventional methods, this method identifies block walls based on geometric features without relying on MMS trajectory data or deep learning inference results. In addition, the computational load is low and manual correction can be minimized. In our experiments, we used point cloud data collected in urban areas in Japan and achieved a precision of 0.750, recall of 0.810, and F-measure of 0.779. The results demonstrate the effectiveness of this method for automatic extraction of block walls and rapid assessment of collapse risk and are expected to contribute to safety measures in areas with high seismic risk.

1. Introduction

In Japan, walls made of stacked concrete blocks (block walls) are widely constructed to demarcate property boundaries, protect privacy, and provide soundproofing. These block walls can be easily damaged by earthquakes. Especially in Japan, a country known for its high frequency of earthquakes, the collapse of these block walls is a major problem. A survey conducted by Ryuta Enokida et al. on the damage caused by the earthquake that occurred off the Noto Peninsula on January 1, 2024 revealed that many block walls collapsed in residential areas, and that many of these walls had not been protected from falling over (Enokida Ryuta et al., 2024). Collapsed block walls do not merely cause damage on the spot; they can also cause secondary hazards and confusion when collapsed walls block roads and impede their function as evacuation routes in the event of a disaster. In order to prevent such a situation from occurring, it is important to understand the current status of block walls in detail and to accurately assess their collapse risk. It is also important to develop an evacuation plan that takes into account the impact after collapse in case of emergency. Therefore, the Ministry of Land, Infrastructure, Transport and Tourism (MLIT) is actively implementing safety measures in cooperation with the national and local governments, such as conducting thorough public awareness campaigns on the removal and renovation of block walls and providing support as a core project through grants and other means (MLIT, 2024).

Against this background, a study by Y. Umehara et al. proposed a new method for identifying block walls and assessing their collapse risk from point cloud data acquired using the Mobile Mapping System (MMS) (Y. Umehara et al., 2021). In this study, detailed movement trajectories of MMS and features related to the shape of the fence are analyzed by deep learning, and a method for extracting block walls is discussed. However, this approach suffers from the problem that points that are not walls are often misidentified as walls, resulting in a lower precision. Therefore, manual correction is indispensable for the extracted results, and this has been pointed out as a problem in terms of practicality. Furthermore, this method, which relies on MMS trajectory data, is difficult to apply to point cloud data for which no trajectory data is provided.

To solve these problems, this study aimed to efficiently extract block walls without using deep learning, using only 3D point cloud data as input and a simpler method based on geometric shape features. This method enables the extraction of block walls in a wider range of situations because it does not rely on MMS trajectory data. Furthermore, it is expected to contribute to efficient and rapid assessment of collapse risk by minimizing manual modifications.

2. Related Work

Existing studies to extract specific road structures from 3D point clouds measured by MMS include identification by analyzing laser light reflection intensity and color information (E. Barçon et al., 2022), (X. Guo et al., 2023), identification based on specific geometry by extracting geometric features (N. H. Arachchige et al., 2012), (Li Y et al., 2016), (M. Yadav et al., 2015), (Li Fashuai et al., 2018) and identification by machine learning and deep learning (Hiroki Matsumoto et al., 2021), (Mikael Reichler et al., 2024).

First, focusing on methods based on reflection intensity and color information, E. Barçon et al. proposed a method for extracting road markings from a road surface point cloud using the difference in reflection intensity between road markings and asphalt (E. Barçon et al., 2022). Xinyu Guo et al. proposed a semantic segmentation method using color information associated with point clouds (X. Guo et al., 2023). These references show that it is possible to identify specific objects from point clouds based on color and reflection intensity information. However, there are few methods that use only color information, and deep learning and geometrical features are the most common methods. In addition, the color information in the MMS point cloud is strongly affected by the presence or absence of shadows, and there are individual differences due to the age of the block walls and the surface coating, making it difficult to determine the color information uniformly.

Next, we turn our attention to geometry-based methods. N. H. Arachchige et al. proposed a method for detecting building facades from MLS point clouds, focusing on methods for detecting potential building clusters, segmenting planar regions based on roughness, and recognizing facade elements based on 2D geometric knowledge (N. H. Arachchige et al., 2012). Li Y. et al. proposed a building facade detection method consisting of the following steps: point cloud projection algorithm with morphological filtering, acquisition of building facade features in image space, transformation of building facade features to 3D space by inverse transformation of point cloud projection, and reconstruction of facade pieces by a restricted facade plane detection algorithm. A method for extraction and simplification of façade parts was proposed (Li Y et al., 2016). M. Yadav et al. proposed a method to detect pole-shaped objects from mobile LiDAR data using Principal Component Analysis (PCA) based analysis (M. Yadav et al., 2015). Li Fashuai et al. proposed a RANSAC-based line fitting and 2D point density-based pole extraction method (Li Fashuai et al., 2018). In this way, by restricting the target geographic feature and searching for the geometry specific to that feature, the geographic feature can be extracted with precision. However, detailed conditions need to be set to extract only block walls, hedges, and fences, which have individual differences in shape, while discriminating landmarks with similar characteristics, such as block walls, hedges and fences.

Finally, focusing on methods based on deep learning. Hiroki Matsumoto et al. proposed a method to identify guardrails with various shapes from MMS point clouds by extracting features from both point clouds and digital images using Convolutional Neural Networks (CNN) (Hiroki Matsumoto et al., 2021). Mikael Reichler et al. proposed a method to semantically segment 3D point cloud data by combining continuous scans without requiring odometry information (Mikael Reichler et al., 2024). These methods based on deep learning have attracted much attention in recent years because of their robust recognition capabilities. However, one challenge is the huge amount of data and processing time required for learning.

3. Point Cloud Extraction of Wall Surface

3.1 Characteristics of MMS Point Clouds

While moving, the MMS acquires cross-sectional profiles at regular intervals using a laser scanner and reconstructs 3D profiles using the position and orientation of the MMS calculated by a GNSS/IMU navigation system. Therefore, the density of the point cloud changes depending on the speed at which the MMS is moving. In addition, there are a variety of MMS models with different specifications. Therefore, the laser scanner installed in each MMS model is different. Therefore, the measurement density in the scan direction and measurement precision depend on the laser scanner installed. Therefore, these features have a significant influence on the threshold values for normal calculation, isolated point removal, and segmentation. The point cloud data used in this study were acquired by an MMS equipped with two laser scanners capable of 360-degree measurement at a 45-degree tilt.

3.2 Proposed Method

This method performs detection based on the shape features of a fence. A fence is a vertical structure. The normal vector of a vertical structure is close to the horizontal direction. In addition, when a point is projected onto the xy-plane, the point is often a straight line. On the other hand, there are many objects whose normal vectors of point clouds are close to horizontal, such as building walls, guardrails, and cars. This method finds the normal vector from a point cloud, extracts point clouds with horizontal normal vectors, and then extracts point clouds that satisfy the wall surface condition. The shape characteristics of the block wall and other objects with similar normal vectors are summarized below.

Block walls: In Japan, the height of walls is legally limited to 2.2 m or less. On the other hand, there are no restrictions on length. The width depends on the thickness of the block, but there are standards for 10 cm, 12 cm, 15 cm, and 19 cm.

Hedges: Often the height is similar to that of a wall. On the other hand, because it is a plant, the surface roughness is greater than that of a block wall because the laser points are removed.

Building walls: Various shapes are available, but they are often taller than walls and consist of many flat surfaces.

Guardrails: They are about 1 m high and are connected to the road surface by posts, so there is a gap between the guardrail and the ground.

Cars: The height varies depending on the type of car, but is often about the same as the height of the wall.
The width of the guardrail differs greatly from that of the wall in terms of size on a flat surface.

Figure 1 shows the processing flow of the proposed method.

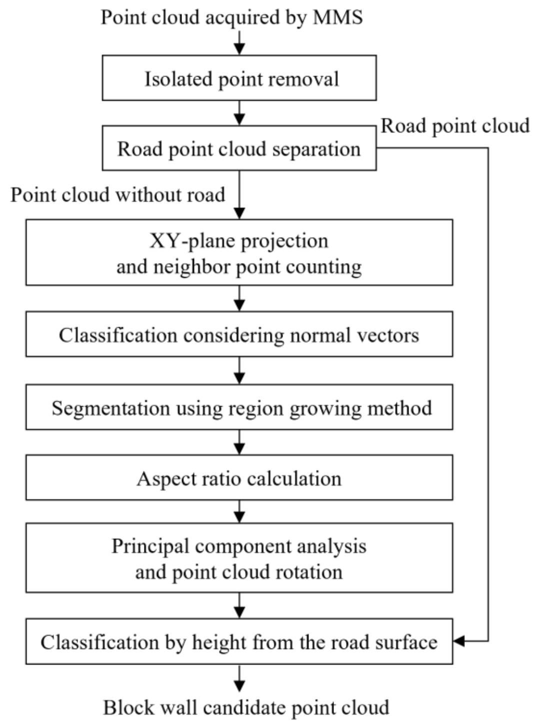

Figure 1. the processing flow

First, the point cloud was separated into a point cloud of road surfaces, C_{road}, and the rest of the point cloud, C_n. The Cloth Simulation Filter (CSF) of W. Zhang et al. was used to separate the road surface (W. Zhang et al., 2016). Isolated points were removed before applying the CSF because noise points, such as aerial, degrade the performance of the CSF. Figure 2 shows an example of the input point cloud and Figure 3 shows an example of the point cloud separated from the road surface by the CSF.
The CSF parameters are Cloth resolution: 0.1, Max iterations: 500, and Classification threshold: 0.1.

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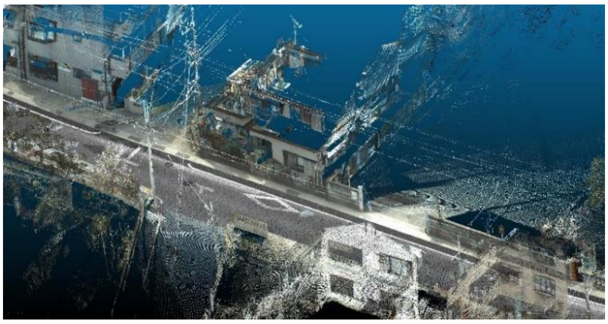

Figure 2. Point cloud before separation

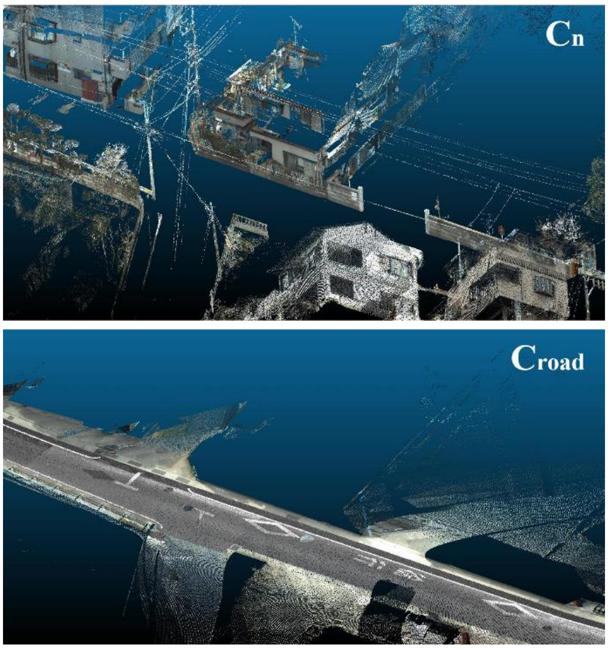

Figure 3. Point cloud after separation

Next, for a point cloud that does not include the road surface, the point cloud is projected onto the xy-plane, as shown in Figure 4. As shown in Figure 5, the MMS used in this study consists of two laser scanners tilted at an angle of 45 degrees to the left and right of the car, with a measurement frequency of 100 Hz per line. Therefore, the spacing of the laser scan lines depends on the speed, and the spacing of points in the height direction also depends on the speed. Therefore, the relationship between the number of points at a given height and the measurement speed of MMS is generally as shown in Figure 6. In other words, for a 1.5-meter-high wall, approximately 15 points will be lined up in the height direction at a speed of 40 km/h. Therefore, by counting the number of neighboring points of a point cloud projected on the xy-plane and extracting 15 or more points, a point cloud other than the wall surface can be largely eliminated. In this paper, we assume that the search area for the neighborhood points has a radius of 3 cm, and that the maximum speed limit in a residential area is 40 km/h. The threshold for the number of neighborhood points is 15 points.

Figure 7 visualizes the number of points in the neighborhood of each point projected onto the xy-plane. Points with less than 15 points are colored black, and points with 15 or more points are colored according to the number of points. The figure shows that the number of points in the vicinity of the block walls and facade facing the road is high. On the other hand, the number of points on the walls and roofs that do not face the road, as well as trees and structures on the building site, are small, and these objects can be removed by this process.

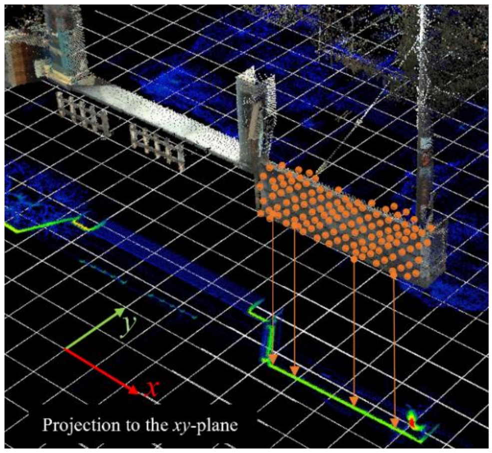

Figure 4. Point cloud projection to the x-y plane

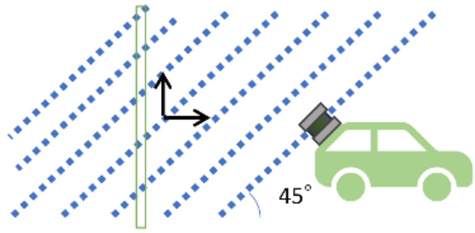

Figure 5. Characteristics of LiDAR measurement by MMS

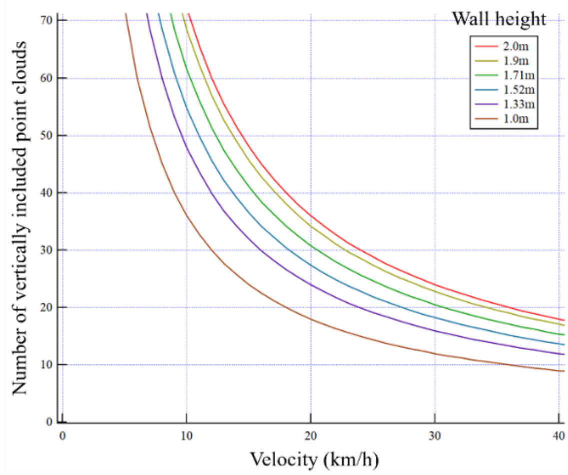

Figure 6. Relationship between the height of the wall and the number of point clouds contained in the vertical direction

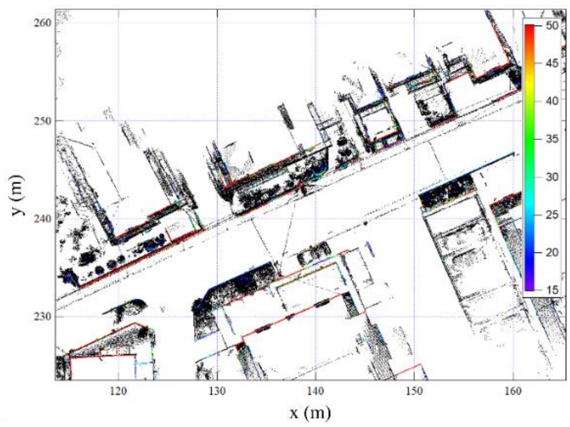

Figure 7. Visualization of the number of vertically contained point clouds

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Next, the normal vector is estimated for the extracted point clouds, and point clouds within 15 degrees of the horizontal are extracted. This process removes many of the point clouds of overhead structures directly above walls and trees that could not be removed in the previous process. At this stage, building walls, utility poles, and cars remain as candidates. Next, in order to remove point clouds other than walls, segmentation is performed using the region growing method. For each segment obtained, we find the smallest box that encompasses all the point clouds in the segment. The smallest box was selected by rotating the box by one degree around the z-axis and selecting the box with the smallest volume. Using this method, the size of the rectangle enclosing the segment is calculated and the ratio of height to width is obtained. (Figure 8)

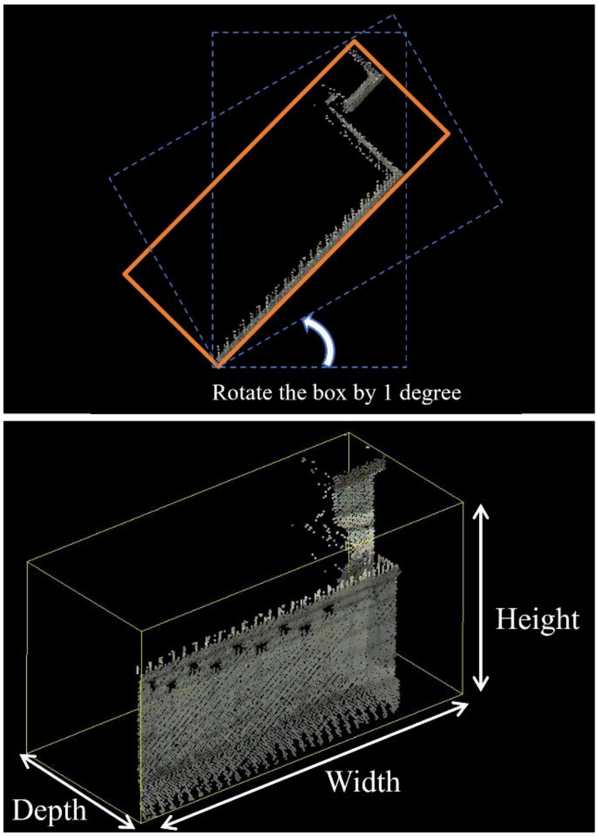

Figure 8. Calculating the aspect ratio of a segmented point cloud

Next, the point cloud is classified by considering the height of the point cloud from the road surface. A series of walls have the same height. Since walls are set from the road surface, there is no gap between the road and the lowest point, except for special fences. On the other hand, guardrails and signboards are, in principle, installed on the road surface by means of legs, so there are gaps between them and the ground at many points on the structures. Figure 9 shows a schematic diagram of the method used to extract the gap between the road surface and the ground. First, the height of the road surface is obtained by first searching for points near the segment in the separated road point cloud. Next, a process is performed to calculate the distribution of the heights of the candidate wall surface points. The first step in this process is to perform a principal component analysis on the point cloud of the horizontal projection of the wall candidate points on xy. Since the longitudinal direction of the wall is the first principal component, the point clouds in the segment are rotated so that the x-axis coincides with the first principal component (Figure 9 (1)). Furthermore, the point cloud is sliced at regular intervals along the x-axis (Figure 9 (2)). In this paper, the slice interval is empirically set to every 0.5m. The minimum and maximum values of the height of the point cloud in the sliced area are obtained. The maximum value is defined as the percentage of points with a height of 2.2 m or less, which is the legal maximum height of walls in Japan, and the minimum value is defined as the percentage of points with a distance of 0.1 m or less from the road surface, and the median value is not far from the road surface.
The candidate points of the wall surface obtained by this method have some minor omissions because some points are excluded from the candidate points due to the effect of the unevenness of the wall surface. Therefore, as a final step, points within 0.15 m of the candidate points are added to the candidate wall surface points, assuming that they are continuous points. This method extracts candidate wall surface points by these filtering processes.

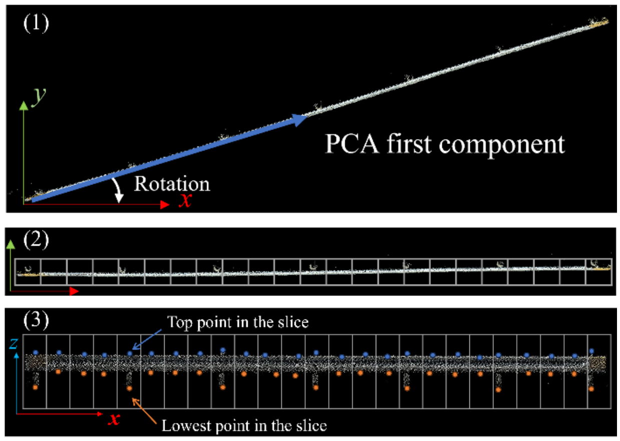

Figure 9. Overview of calculation method for height distribution

4. Automatic Extraction Experiment of Block Walls

4.1 Experimental Methods

In this experiment, the point cloud data of manually classified block walls is used as the correct data, and its accuracy is evaluated by comparing it with the results extracted by the proposed method. The metrics used in the evaluation are precision, recall, and F-measure. The precision is the percentage of automatically extracted points that are correctly identified as block walls and indicates the accuracy of the system. The recall rate is the percentage of automatically extracted points out of the entire block wall and indicates the comprehensiveness of the system. The F-measure is calculated as the harmonic mean of the precision and recall and is used to confirm that both the precision and recall are high.

4.2 Experimental Conditions

A point cloud of the urban area around Arika Shrine in Ebina City, Kanagawa Prefecture, Japan, including various geographic features such as block walls, hedges, and fences, was used as the evaluation data. The MMS used to acquire the point clouds was equipped with two laser scanners tilted at an angle of 45 degrees to the left and right of the car. The point cloud used for the evaluation was a point cloud of a road extension of approximately 800 m, and the number of point clouds was 25069249. The overall image of the evaluation data is shown in Figure 10. The block walls selected for this evaluation were those consisting only of blocks, and those containing partial hedges, fences, stone walls, etc. The counting method of block walls was based on the following formula. In addition, we counted each consecutive block wall as a single block wall, regardless of its length.

Figure 10. Test field point cloud

4.3 Experimental Results and Discussion

Figure 11 and Figure 12 show the point clouds before and after the extraction, respectively. Table 1 shows the results of the total of the extracted point clouds, and Table 2 shows the evaluation results calculated based on the total of the extracted point clouds. Of the 63 block walls to be extracted, 51 could be extracted by the proposed method and 12 could not. In addition, there were 17 cases where structures other than block walls were extracted as block walls. As a result, the precision, recall, and F-measure were 0.750, 0.810, and 0.779, respectively.

Object name	Exist	Extracted
Block wall	35	28
Block wall including fence	23	21
Block wall including hedge	1	1
Block wall including stone wall	4	1
Fence	12	8
Hedge	8	6
Other	3	3

Table 1. Aggregate results of extracted objects

Evaluation index	Value
True positive	51
False positive	17
False negative	12
Precision	0.750
Recall	0.810
F-measure	0.779

Table 2. Assessment Results

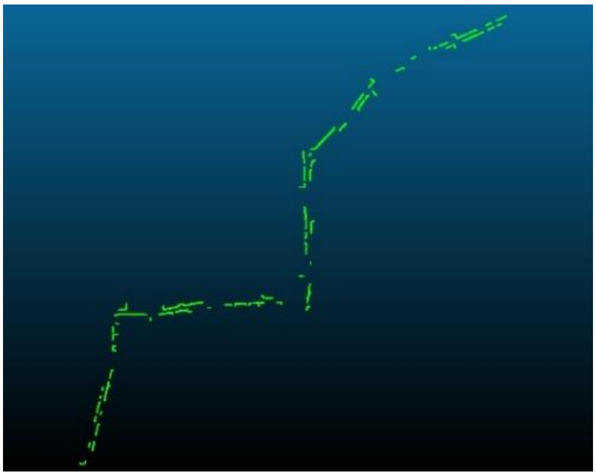

Figure 11. Result of wall extraction.

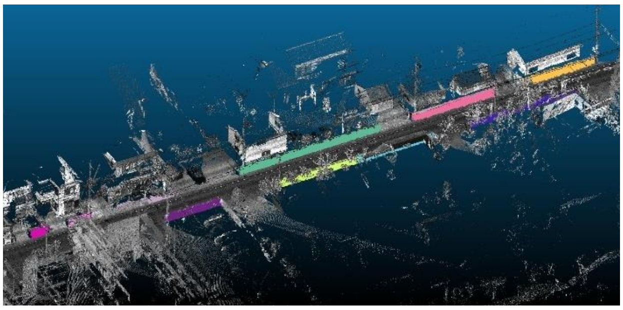

Figure 12. Result of wall extraction.

Although the method proposed in this study considered only geometrical features, both precision and recall were of a similarly high level. However, there are some issues. First, the method was only able to extract one of the four block walls that included a stone wall. The reason for this is that the block and stone wall portions were separated during segmentation, as shown in Figure 13. This may have resulted in the objects being judged as not being located on the road surface and removed in the process of comparing the positional relationship between the block and the road surface point cloud.

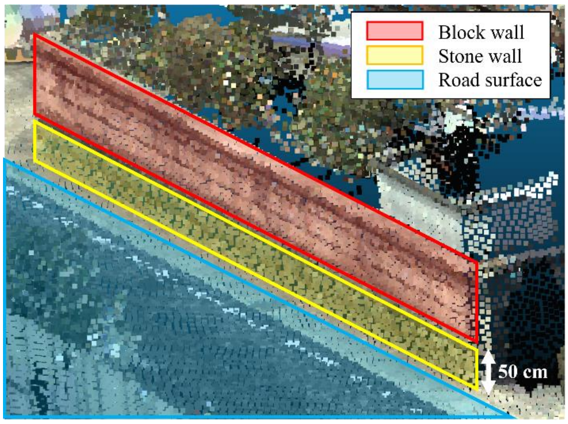

Figure 13. Example of objects other than block walls extracted

Next, we looked at the factors that contributed to the low precision, and found that many fences and hedges were misidentified as block walls, with 8 fences and 6 hedges out of the 17 misidentified fences and hedges. These structures are similar to block walls in use and general shape, and in some cases they are used in combination with block walls, as shown in Figure 14. Therefore, in cases where a fence gate was attached between two block walls, we recognized them as the same segment and extracted the part of the fence gate that should not have been extracted as a part of the block wall. In addition, the proposed method alone cannot classify objects that have many geometrical similarities with block walls, such as fine-grained fences and well-maintained hedges. In the case of a hedge, a part of the laser beam reaches the inside of the hedge, so the dispersion of the point cloud near the hedge tends to be larger than that of the point cloud of a block wall acquired under the same conditions. However, the measurement precision of MMS depends on the GNSS reception and measurement speed, even within the range of a single run, making it difficult to remove point clouds of hedges over a wide area with the same threshold value. At a fence, a portion of the laser beam does not hit the wall but hits an object behind it, resulting in missing point clouds. In such cases, the fence could be removed by evaluating the continuity of points in each scan line of the laser. However, this method requires only a three-dimensional point cloud as input, so it is difficult to classify fences at this time.

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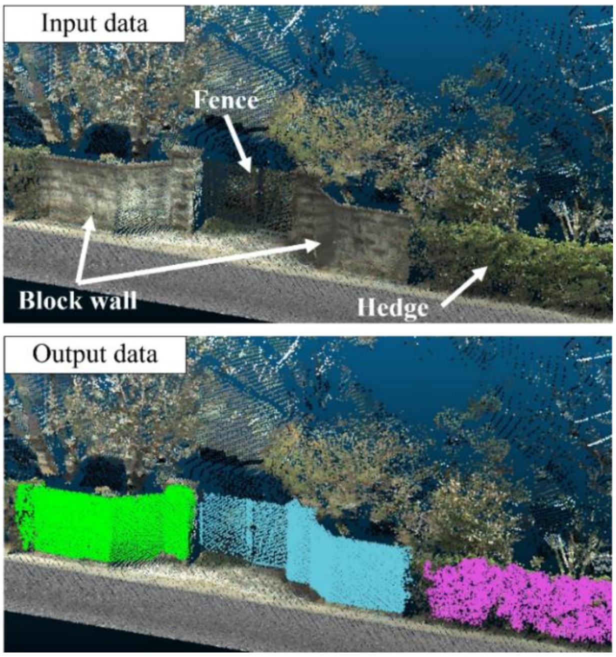

Figure 14. Block walls including stone walls that were not extracted by the proposed method

Conclusion

To reduce the risk of block walls collapsing in urban areas in Japan, a country with frequent earthquakes, this study proposes a method to extract block wall sections from 3D point cloud data measured using the Mobile Mapping System (MMS). This method focuses on geometric features and can identify block walls in a wider range of situations without using decision materials other than point cloud coordinate information, such as driving record data or inference results from deep learning.

In the experiment, the performance of the proposed method was evaluated using point cloud data around Ebina City, Kanagawa Prefecture. The results showed that the recall was as high as 0.810, but the precision was slightly lower at 0.750. One of the reasons for this is that in many cases, geographic features similar to block walls, such as fences and hedges, were not clearly identified as block walls and were incorrectly extracted. In addition, although the data used in this study did not include a large number of block walls, block walls including stone walls could not be extracted with a high probability. This raises the concern that both precision and recall may be greatly affected by the environment in which the verification is conducted. These issues are areas that require further improvement in future research.

In the future, additional feature extraction methods and improved segmentation algorithms should be developed to improve the precision of this method. In addition, we aim to validate the proposed method using data from multiple environments in the future to confirm that it can perform equally well in a wider range of environments. We hope that the results of this study will be useful as a safety measure in areas with high seismic risk.

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