Sensors and Materials, Vol. 34, No. 7 (2022) 2625–2635
MYU Tokyo

S & M 2995

Automatic Construction of Road Lane Markings Using Mobile Mapping System Data

In-Ha Choi and Eui-Myoung Kim*

Department of Spatial Information Engineering, Namseoul University,
91, Daehak-ro, Seonghwan-eup, Seobuk-gu, Cheonan, Chungcheongnam-do 31020, Korea

(Received February 22, 2022; accepted April 26, 2022: online published, May 30, 2022)

Keywords: high-definition maps, deep learning, road lane marking, digitizing, structural editing, quality test

There is growing demand for high-definition maps to improve the stability of current autonomous driving technology. However, the current process for building high-definition maps involves a high proportion of manual labor for digitizing and structural editing, making it difficult to maintain road conditions that frequently change. Moreover, as the quality of a high-definition map varies with the skill of the person creating it, it is difficult to achieve consistency. Accordingly, in this study, we propose a methodology that extracts areas of road lane markings from point clouds acquired by mobile mapping systems. The methodology uses a deep learning model to predict the color type of road lane markings, then automatically generates a high-definition map layer. Positioning accuracy and vector structuring tests were performed to verify the usability of the road lane marking vector data generated using the proposed methodology. In the positioning accuracy test, the maximum error for the horizontal and vertical positions was within 0.2 m and the root mean square error at the 95% confidence level was within 0.1 m for the original and generated vector data. In the vector structuring test, both study areas showed a high structuring accuracy of 85% or more.

1. Introduction

Current autonomous driving technology relies on vehicle sensors such as cameras and GPS. However, to increase stability, there is a growing need for high-definition maps when the sensors fail to recognize the environment. High-definition maps provide road data such as lanes, signs, and road facilities necessary for autonomous driving based on precise 3D positioning information.[1,2] Building a high-definition map requires the collection of high-precision data through mobile mapping systems (MMSs) that combine various sensors, followed by digitizing and structural editing.[3] However, as digitizing and structural editing require significant manual labor, there are time and cost limitations for constructing road maps nationwide.[4] To solve this problem, public and private organizations have launched joint projects to build high-definition maps in Korea; however, the quality of high-definition maps depends on the skill of the person

*Corresponding author: e-mail: kemyoung@nsu.ac.kr
https://doi.org/10.18494/SAM3872

ISSN 0914-4935 © MYU K.K.
https://myukk.org/

creating them.[5] Therefore, there is a need for technologies that can automatically build high-definition maps as an alternative to traditional manual construction systems.

Existing studies on building high-definition maps to support autonomous driving have applied a variety of techniques. High-definition maps are typically built through MMS surveying; however, to address the limitations of MMS equipment such as occluded areas and GPS multipath, which mainly occur in urban areas with a high density of high-rise buildings, researchers have conducted studies on generating basic data to construct high-definition maps by matching aerial photos with MMS data.[6,7] There have also been studies on detecting and classifying road lane markings by combining spatial data acquired through monocular cameras (e.g., MMS, black box) with AI to automate manual high-definition map construction systems.[8–10] In addition, researchers have proposed a technique that automatically detects spatial relationship errors such as self-overlapping, vertex overlapping, and unclosed polygons to inspect high-definition maps.[11]

Most research on high-definition maps has been focused on automating their inspection or generating basic data using aerial photos to supplement the limitations of MMS equipment, whereas there has been insufficient study on automating the digitizing and structural editing processes. Furthermore, research on automating digitizing and structural editing has mainly involved detecting and classifying road lane markings through an image-based deep learning model using color information. However, as color is sensitive to brightness, detection of the object of interest is limited when the collected point clouds between two consecutive tracks differ in brightness. Accordingly, in this study, we focused on road lane marking objects, which are essential for autonomous driving and consume the most time in digitizing and structural editing. The purpose of this study was to automate the digitizing and structural editing of road lane markings using a deep learning model that extracts the area of the road lane marking based on point clouds acquired by an MMS and is trained using not only color information but also geometric information.

2. Methodology and Materials

2.1 Methodology

The objectives of this study can be divided into three detailed steps as shown in Fig. 1.

The goal of the first step is to link a point cloud acquired via an MMS and the converted intensity image to extract the area of the road lane marking, for which ground point classification, image reclassification, and polygon classification are performed.

The goal of the second step is to extract only the point cloud corresponding to the road lane marking in the original point cloud based on the area of the road lane marking extracted in the first step and automatically classify the color of the road lane marking using a deep learning model.

The goal of the third step is to automate the digitizing and structural editing processes based on the road lane marking's area information and color types predicted through the deep learning model. To draw the road lane markings, automatic digitizing, centerline extension, and direction

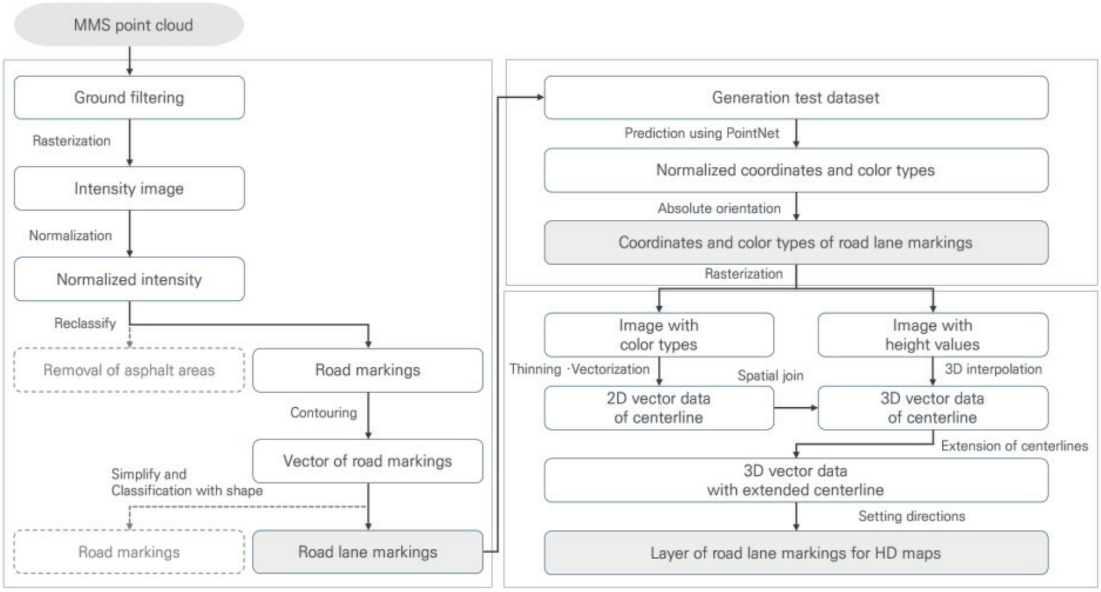


Fig. 1. Methodology of automatic digitizing and structural editing of road lane markings for high-definition maps.

setting are performed, and the color information predicted through deep learning is input as attributes to automatically generate the road lane marking layer.

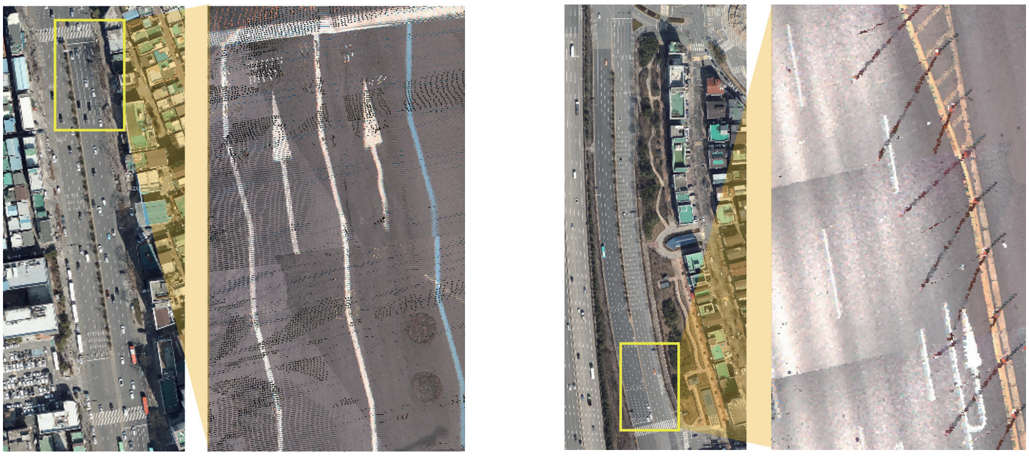
2.2 Study areas

Figure 2 shows the study areas, which were general roads of eight lanes or more in Seongnam-si, Gyeonggi-do. Study area A is an inclined road in an urban center containing zigzag lanes that indicate a low speed. Study area B is a curved road containing reversible lanes for U-turns and left turns through the median. Table 1 shows the area and number of points of the two study areas.

The input data used in the study consisted of point clouds acquired in March 2020 using a Pegasus:Two Ultimate MMS (Leica). The data contains 3D coordinates (*XYZ*), color information (RGB), and intensity information (I). The horizontal and vertical collection accuracies of the point clouds acquired by the MMS are 2 and 1.5 cm, respectively, and the point density of the two study areas is approximately 2100 points/m^2 or more.

3. Application and Analysis

A Python script was developed to automate the proposed methodology for extracting the road lane marking areas and digitizing and structural editing of the road lane markings. Spatial data analysis and data format conversion were performed using various libraries, such as the ArcPy library in the commercial software ArcGIS Pro 2.6.0, WhiteboxTools, CloudCompare, and Scikit-learn, which has a K-nearest neighbors algorithm.



(a) (b)

Fig. 2. (Color online) (a) Study area A and (b) study area B.

Table 1
Characteristics of study areas.

Study area	Road characteristics	Number of lanes	Area (m)	Number of points
A	Inclined	10	70 × 201	32760415
B	Curved	10	62 × 295	37869029

3.1 Extraction of road lane marking areas

The point clouds acquired by the MMS contain ground points such as roads and non-ground points such as buildings and trees.[12] Since the road lane markings (the objects of interest) are on the ground, an adaptive TIN (ATIN) filtering technique that removes non-ground points using Delaunay triangulation was used, and its results are shown in Fig. 3.

To efficiently remove asphalt from the road, the information of the ground points remaining after ground filtering was converted into an image, and the image was reclassified. A previous study reclassified the image using its RGB color and intensity information; however, as RGB color information is sensitive to light, the asphalt was not effectively removed when there was a large difference in brightness between the tracks in the MMS data collection environment.[9] As a solution to this problem, utilizing the fact that the road markings have higher intensity than asphalt, in this study, we reclassified the images on the basis of the normalized intensity and generated outline vector data of the road markings through contouring as shown in Figs. 4(a) and 4(c).[13] In the generated road markings, there are polygonal objects such as arrows and linear objects such as road lane markings. To classify only the linear objects, the number of interior angles greater than 180° was identified; if an object had two or more such angles, it was classified as a candidate polygonal object, and if the ratio of the length to the area of the polygon was smaller than a certain threshold, it was determined to be a polygonal object and removed. The classified linear objects are shown in Figs. 4(b) and 4(d).

Fig. 3. (Color online) (a) Side view of original point clouds of study area A, (b) side view of original point clouds of study area B, (c) side view of ground points of study area A, and (d) side view of ground points of study area B.

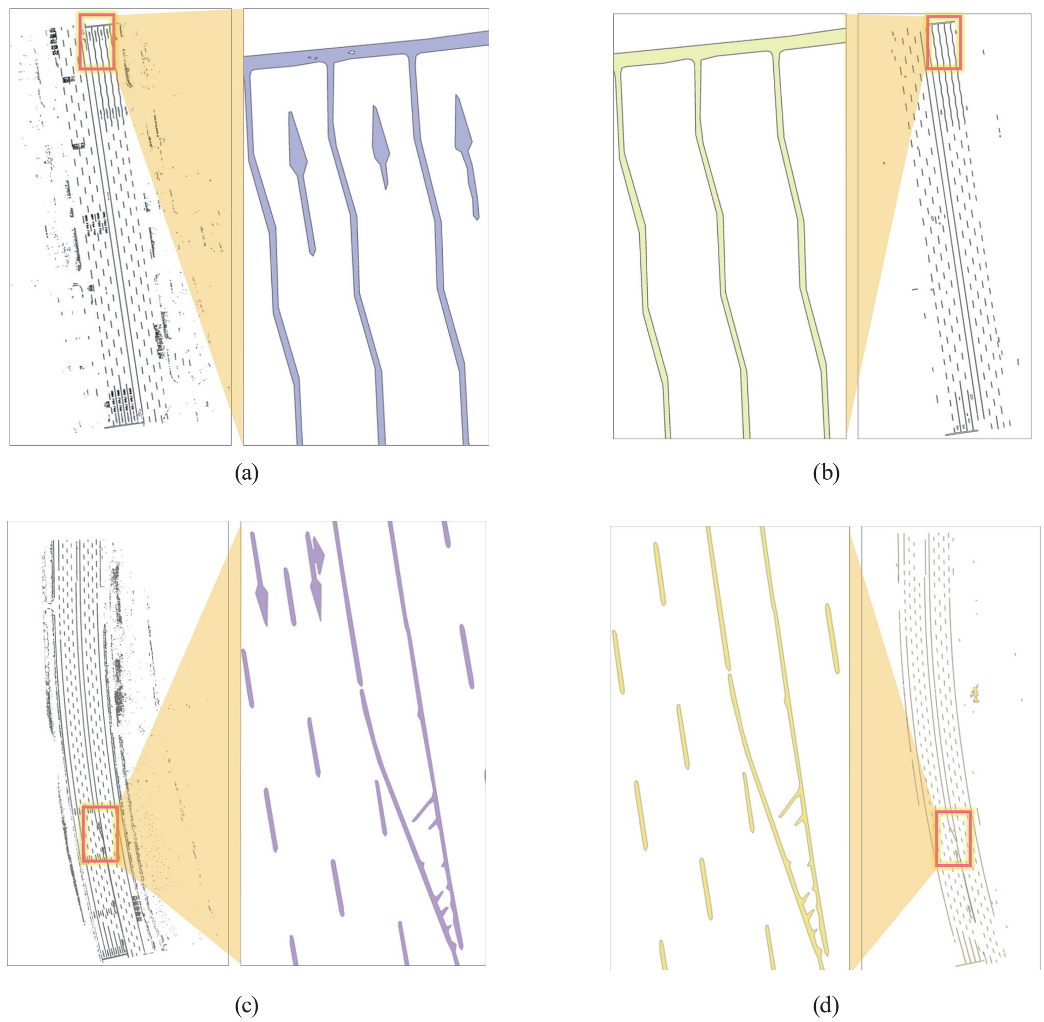


Fig. 4. (Color online) (a) Extracted contours in study area A, (b) classified linear objects in study area A, (c) extracted contours in study area B, and (d) classified linear objects in study area B.

3.2 Classification of road lane marking types

To automate the structural editing of the road lane markings, the color (white, blue, yellow) type was predicted using a deep learning model. PointNet was selected for the deep learning model, which uses not only color information but also geometric information for training.(14) PointNet has a disadvantage that it takes a longer time to train than the image-based deep learning model due to its large amount of training data, but it has the advantage of being able to train in a simple and unified structure by using the point cloud as input data. Table 2 shows the training data and parameters used to train the deep learning model.

The PointNet model was trained with 40 repetitions, resulting in a training accuracy of 99.977%. For the test dataset of the PointNet model, the point cloud corresponding to the road lane markings extracted from the original point cloud based on the area generated in the first step was input. Figure 5 shows the color type prediction results for the two study areas using the

Table 2
Training data and parameters of PointNet model.

Training dataset			Batch size	Epoch
White	Blue	Yellow		
1498	531	2764	24	40

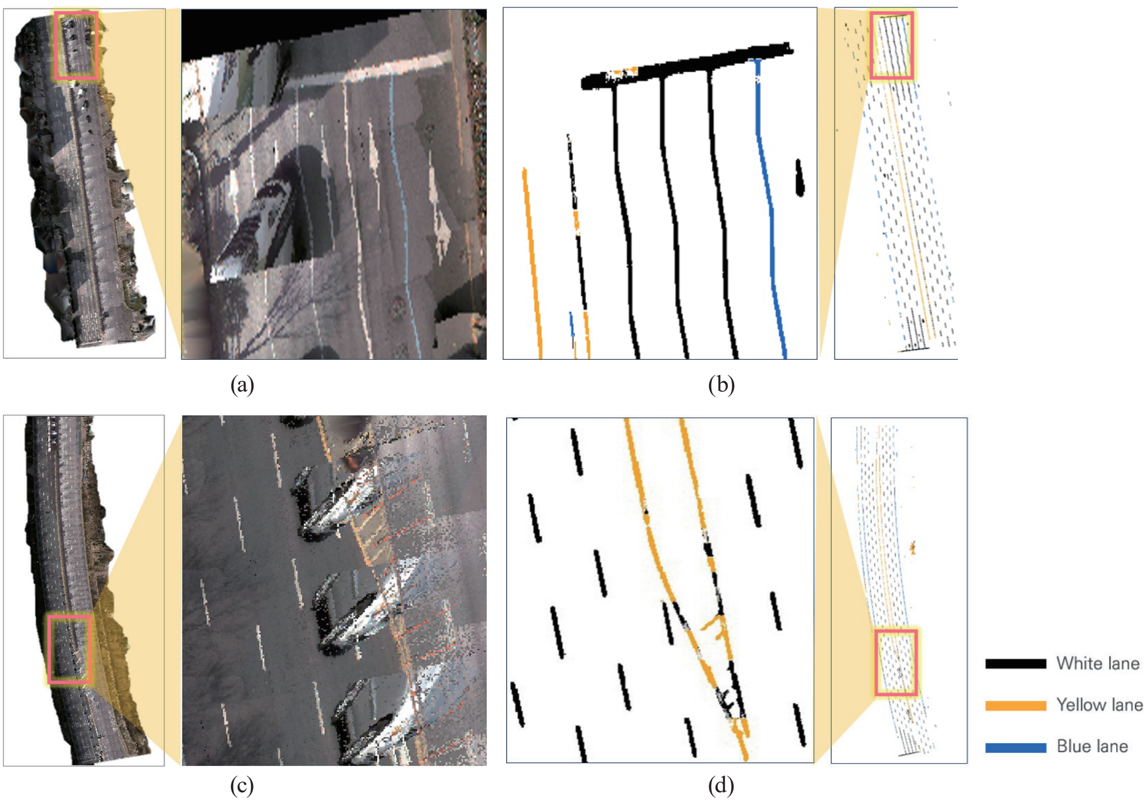


Fig. 5. (Color online) (a) RGB image of study area A, (b) result of prediction of study area A, (c) RGB image of study area B and (d) result of prediction of study area B.

pre-trained model. The prediction accuracies were 89.326 and 80.150% for study areas A and B, respectively, indicating that there is no problem with classification of color type. As the results predicted by the PointNet model are stored as normalized *XYZ* coordinates, absolute orientation was performed to restore the original coordinate system.

3.3 Automation of road lane marking digitizing and structural editing

After classifying the road lane marking types based on the PointNet model, the classified color types and height information were converted into images to draw the centerlines. The centerlines of the road lane markings were then drawn using the thinning method based on the color type images, and the color type attributes of the linear objects were input through a spatial join.[15] As the linear objects generated on the basis of the color type images are 2D, they were converted into 3D objects through 3D interpolation using height images.[16] Next, to show the continuity of the road lane markings, the centerline that connects the centers of the broken and solid lines was extended.

We confirmed that the line extension tool provided by ArcGIS Pro expands not only the lanes on the same line but also adjacent lanes, causing vectorization errors. Therefore, in this study, we proposed an algorithm that selects and expands the lane that is larger than the predefined angle threshold after calculating the slope between the start point and end point of the query object and the start point of the adjacent object using the geometry of the linear object as shown in Fig. 6. After extending the line, the length information and color-type information were combined to automatically input attributes necessary for the road lane marking layer as stipulated by the National Geographic Information Institute. Finally, to set the vehicle direction to northbound or southbound, the northbound and southbound directions of the centerline were first set, and the directions of the remaining lanes were determined on the basis of the southbound centerline. Figure 7 shows the road lane marking layers automatically generated using the proposed methodology. As shown in Fig. 7(a), even though study area A was inclined, the road lane marking layer was generated in three dimensions, and the attributes of the selected bus-only lane object were input according to the high-definition map construction manual: the

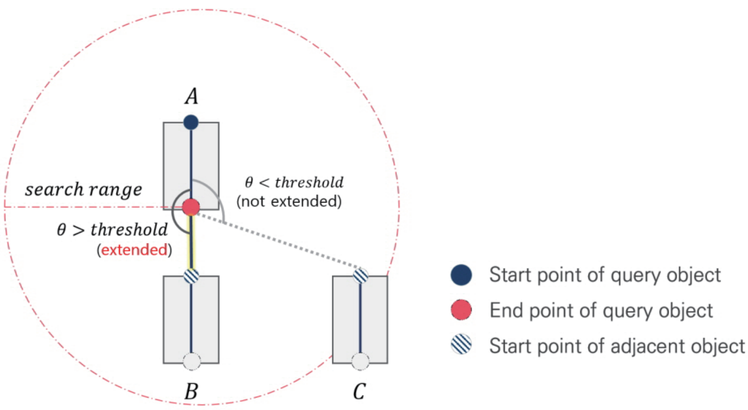


Fig. 6. (Color online) Line extension algorithm using the geometry of the linear object.

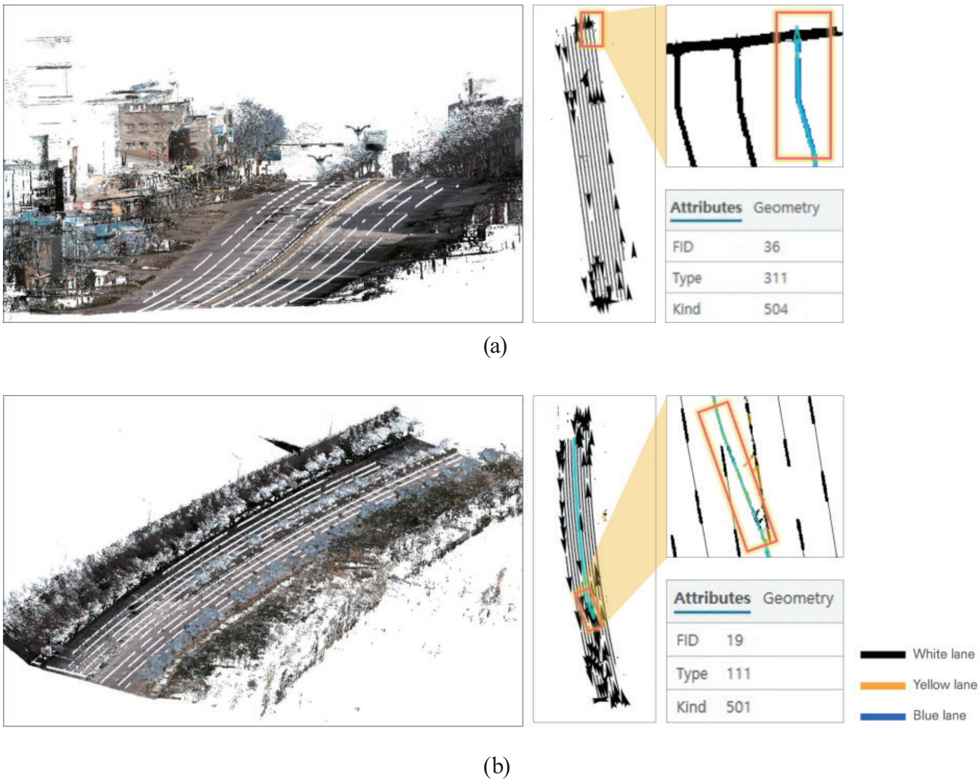


Fig. 7. (Color online) Road lane marking layers of (a) study area A and (b) study area B.

type attribute was a blue single solid line (type:311) and the kind attribute was the bus-only lane (kind:504). As shown in Fig. 7(b), even though study area B was a curved road, the road lane marking layer was drawn according to the road's characteristics, and the attributes of the selected centerline object were input as follows: the type attribute was a yellow single solid line (type:111) and the kind attribute was a centerline (kind:501).

3.4 Verification of road lane marking layer usability

To verify the usability of the road lane marking layers automatically generated using the proposed methodology, we examined whether they satisfied the quality test standards published by the National Geographic Information Institute.(17) For the quality tests, positioning accuracy, object validation, geometric integrity, and vector structuring tests were performed.

To inspect positioning accuracy, four comparison points were set for each study area, and the horizontal and vertical positions of the vector data generated on the basis of the original point cloud were compared. In accordance with quality test standards published by the National Geographic Information Institute in Korea, one comparison point per kilometer was set to determine the positioning accuracy, then the coordinates were compared. All the study areas were within 300 m, but four comparison points were set to perform a more accurate positioning accuracy test. Table 3 shows the results of the positioning accuracy test. The maximum error for the horizontal and vertical positions was within 0.2 m and the root mean square error (RMSE) at

Table 3
Positioning accuracy test for each study area using comparison points.

Study area		Min error	Max error	Average error	RMSE
A	Horizontal	0.0220	0.0830	0.0548	0.0610
	Vertical	0.0005	0.0044	0.0023	0.0030
B	Horizontal	0.0264	0.0926	0.0588	0.0634
	Vertical	0.0010	0.0077	0.0045	0.0051

the 95% confidence level was within 0.1 m, indicating that the positioning accuracy criteria were satisfied.

Table 4 shows the results of the object validation test, where the numbers of omitted objects, geometric type errors, and description position errors were analyzed. The test results showed that most of the omitted road lane marking objects were lanes located at the edge of the road, such as bus-only and parking lanes, and had a low density. Geometric-type errors can be analyzed by determining the number of polygonal objects included due to errors among the road lane markings, which are linear objects. Study area A included two arrows and one object outside the road surface, while study area B included left-turn and U-turn arrows whose line portions were classified as linear objects. In the description position test, no errors were detected in study areas A and B.

The geometric integrity test identifies whether there are multi-parts, vertex overlaps, and so forth. No errors occurred in study area A, indicating its suitability, whereas in study area B, one error occurred where the road lane marking objects intersected.

The vector structuring test is used to inspect the attributes of vector data and was performed by categorizing the data by type and kind attributes, which are essential attributes for road lane markings. Table 5 shows the structuring accuracy and Kappa coefficients for type and kind attributes in study areas A and B. According to the vector structuring test, the structuring accuracy of both study areas was at least 85%, and the Kappa coefficient, which measures the agreement between the actual type and the type input as the attribute, was at least 80%. Hence, the usability of the vector data generated using the proposed methodology was verified.

Table 4
Results of object validation test for each study area.

Study area	Number of original road lane markings	Number of extracted road lane markings	Extraction rate (%)	Number of omitted road lane markings	Omission rate (%)	Geometric type errors	Description position errors
A	181	167	92.27	14	7.73	3	0
B	253	230	90.91	23	9.09	2	0

Table 5
Vector structuring test for each study area.

Study area	Attribute	Structuring accuracy (%)	Kappa coefficient (%)
A	Type attribute	87.879	82.790
	Kind attribute	90.909	87.372
B	Type attribute	88.136	82.619
	Kind attribute	89.831	84.068

4. Conclusions

We proposed a methodology to automatically generate road lane marking layers by combining spatial data and a deep learning model based on point clouds acquired by an MMS. The following conclusions were drawn.

First, rather than using the original point clouds to extract the areas of the road lane markings, the non-ground points were removed, and only about 2% of the original point cloud was applied to the deep learning model through image reclassification and polygon classification, thus improving efficiency.

Second, we proposed a methodology that uses a deep learning model to automate the structural editing of road lane markings. It adopted the PointNet model, which uses not only color information but also geometric information for training, thus enabling the attribute information to be automatically used as the input. In a vector structuring test, study areas A and B both yielded good results with structuring accuracy of 85% or more.

Third, we proposed a methodology for digitizing and extending the centerline by combining the area and predicting the color type of the road lane marking. To verify the usability of the automatically generated road lane marking layers, we analyzed whether they met the quality test criteria for high-definition maps. In the generated vector data, the maximum error for the horizontal and vertical positions was within 0.2 m and the RMSE at the 95% confidence level was within 0.1 m, indicating that the positioning accuracy criteria were satisfied.

The proposed methodology was used to automate some high-definition map construction targets, thereby resolving the inconvenience of manual construction. Future research on expanding the scope of targets that can be automatically constructed will facilitate the construction and updating of high-definition maps for national roads.

References

1 F. Poggenhans, J. Pauls, J. Janosovits, S. Orf, M. Naumann, F. Kuhnt, and M. Mayr: Proc. 2018 21st Intelligent Transport Systems Conf. (IEEE, 2018). https://doi.org/10.1109/ITSC.2018.8569929
2 R. Liu, J. Wang, and B. Zhang: J. Navig. **73** (2020) 324. http://doi.org/10.1017/S0373463319000638
3 National Geographic Information: https://www.ngii.go.kr/kor/main.do (accessed February 2022).
4 Y. K. Park, W. P. Kang, J. E. Choi, and B. J. Kim: J. Korean Assoc. Geog. Inf. Stud. **22** (2019) 146. https://doi.org/10.11108/KAGIS.2019.22.3.146
5 J. H, Seol, W. J. Lee, Y. S. Choi, and I. H. Jeong: J. Korean Assoc. Geog. Inf. Stud. **22** (2019) 133. https://doi.org/10.11108/kagis.2019.22.3.133
6 M. Javanmardi, E. Javanmardi, Y. Gu, and S. Kamiljo: Remote Sens. **9** (2017) 975. https://doi.org/10.3390/rs9100975
7 T. S. Choi, H. S. Yoon, Y. S. Choi, W. J. Lee, and S. Y. Chang: J. Korean Assoc. Geog. Inf. Stud. **28** (2020) 69. http://dx.doi.org/10.7319/kogsis.2020.28.3.069
8 W. J. Jang, J. H. An, S. Y. Lee, M. H. Cho, M. K. Sun, and E. T. Kim: Proc. 2018 IEEE Intelligent Vehicles Conf. (IEEE, 2018). 1931.
9 I. H. Choi and E. M. Kim: J. Korean Soc. Surv. Geodesy Photogramm. Cartogr. **39** (2021) 133. https://doi.org/10.7848/ksgpc.2021.39.3.133
10 T. Y. Lee, M. H. Jeong, and A. Peter: Sens. Mater. **34** (2022) 251. https://doi.org/10.18494/SAM3732
11 S. P. Hong, J. M. Oh, Y. H. Song, Y. M. Shin, and D. K. Sung: J. Korean Soc. Surv. Geodesy Photogramm. Cartogr. **38** (2020) 391. https://doi.org/10.7848/ksgpc.2020.38.4.391
12 L. Chen, X. Fan, and X. Du: Proc. 2014 8th Earth and Environmental Science Conf. (IOP, 2014). https://doi.org/10.1088/1755-1315/18/1/012028

13 H. Guan, J. Li, Y. Yu, C. Wang, M. Chapman, and B. Yang: Remote Sens. **87** (2014) 93. https://doi.org/10.1016/j.isprsjprs.2013.11.005
14 R. Q. Charles, S. Hao, M. Kaichun, and J. G. Leonidas: Proc. 2017 IEEE Computer Vision and Pattern Recognition Conf. (IEEE, 2017) 1063.
15 I. H. Choi and E. M. Kim: J. Korean Soc. Surv. Geodesy Photogramm. Cartogr. **39** (2021) 363. https://doi.org/10.7848/ksgpc.2021.39.6.363
16 I. H. Choi: Master Thesis, Application of Deep Learning for Automatic Construction of Road Lane Markings in High-Definition Road Maps (Namseoul University, Republic of Korea, 2021).
17 National Geographic Information: HD Map Quality Test Manual, https://www.ngii.go.kr/kor/contents/view.do?sq=1196&board_code=contents_data (accessed February 2022).

About the Authors

In-Ha Choi received her B.S. degree from Namseoul University, Korea, in 2018. From 2017 to 2020, she worked at Geospatial Information Technology (GIT). She received her M.S. degree in spatial information engineering from Namseoul University, Korea, in 2022. Her research interests are in photogrammetry, artificial intelligence (AI), and GIS. (cso8892@naver.com)

Eui-Myoung Kim received his B.S. and M.S. degrees from Gyeongsang National University, Korea, in 1994 and 1996, respectively, and his Ph.D. degree from Yonsei University, Korea, in 2000. From 2000 to 2002, he was a senior researcher at Korea Institute of Civil Engineering and Building Technology (KICT). He worked as a postdoctoral fellow at the University of Calgary, Canada, from 2003 to 2005. He was with Korea Geospatial Information and Communication (KSIC) from 2005 to 2006. Since 2007, he has been a professor at Namseoul University, Korea. His research interests are in photogrammetry and GIS. (kemyoung@nsu.ac.kr)