AUTOMATED LOCALIZATION AND FUNCTIONAL CONDITION ASSESSMENT OF ADA CURB RAMPS WITH MOBILE LIDAR POINT CLOUDS

FINAL DRAFT

by

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16. Abstract

Curb ramps are an essential component of safe, accessible, and efficient mobility for all transportation users. To make sure that curb ramps can function as intended, their design and construction should meet Americans with Disabilities Act (ADA) standards and guidelines, given that those with disabilities are most adversely affected by improper curb ramp construction. Missing curb ramps, as well as those that do not meet the requirements, may cause accessibility barriers for persons with disabilities. One of the primary challenges that transportation agencies face is that assessing the quality of curb ramps is time-consuming and labor intensive, especially because every corner at an intersection includes multiple curb ramps.

Mobile light detection and ranging (lidar) is a remote sensing technology that provides detailed 3D geometry information in the form of 3D point clouds, which can be used to extract various characteristics and metrics to determine the ADA compliance of curb ramps. However, manual processing of mobile lidar data can often be tedious and time-consuming and requires specialized software and training. These issues prevent agencies from using lidar for assessing curb ramp ADA compliance. Therefore, the research team developed an automatic workflow process to extract and localize curb ramps within a large data point cloud. The proposed approach consists of three steps: ground filtering, curb detection, and curb ramp localization. It was evaluated both qualitatively and quantitatively with a mobile lidar data set. The recall, precision, and F-1 scores were all 72.4 percent. The proposed approach can be potentially used for further analysis, such as feature characterization and point cloud classification of other features.

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SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
°F	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	°C
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS FROM SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
°C	Celsius	1.8C+32	Fahrenheit	°F
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

*SI is the symbol for the International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380. (Revised March 2003)

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LIST OF ABBREVIATIONS

ADA:	Americans with Disability Act
Lidar:	Light detection and ranging
MLS:	Mobile laser scanning
ODOT:	Oregon Department of Transportation
PacTrans:	Pacific Northwest Transportation Consortium
PCA:	Principal component analysis
WSDOT:	Washington State Department of Transportation

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EXECUTIVE SUMMARY

Curb ramps are an essential component of safe, accessible, and efficient mobility for all transportation users. To make sure that curb ramps can function as intended, their design and construction should meet Americans with Disabilities Act (ADA) standards and guidelines, given that those with disabilities are most adversely affected by improper curb ramp construction. Missing curb ramps, as well as those that do not meet the requirements, may cause accessibility barriers for persons with disabilities. One of the primary challenges that transportation agencies face is that assessing the quality of curb ramps is time-consuming and labor intensive, especially because every corner at an intersection includes multiple curb ramps.

Mobile lidar is a remote sensing technique that has been adopted by several transportation agencies to regularly collect dense 3D point cloud with high accuracy and efficiency for a wide variety of applications (e.g., asset management, civil design, etc.). Leveraging mobile lidar technology can substantially improve the conventional procedure of asset management. However, there is still a need for automatic tools to process the mobile lidar data effectively and efficiently.

In this project, the research team developed an automatic workflow procedure to extract and localize curb ramps within a large data point cloud. The proposed approach consists of three steps: ground filtering, curb detection, and curb ramp localization. It was evaluated both qualitatively and quantitatively with a mobile lidar data set. The recall, precision, and F-1 scores were all 72.4 percent. The proposed approach can be potentially used for further analysis, such as feature characterization and point cloud classification of other features.

CHAPTER 1 INTRODUCTION

Curb ramps that meet Americans with Disability Act (ADA) requirements are an essential part of a safe and efficient transportation network that needs to be inclusive for persons with disabilities. To make sure that curb ramps can function, design and construction should follow ADA standards and guidelines. Unfortunately, there are many instances where curb ramps fail to meet ADA standards. For example, an audit completed in 2018 (revised in 2019) by the Oregon Department of Transportation (ODOT) showed that only 3 percent of the curb ramps on state highways in Oregon were rated as “good,” while curb ramps were missing in 20 percent of cases (figure 1.1). Curb ramps that are missing or in a poor functional condition may cause accessibility barriers for persons with disabilities.

One of the primary challenges that transportation agencies face is that assessing the quality of curb ramps is usually time-consuming and labor intensive, especially because every street corner at an intersection includes multiple curb ramps. Consequently, it is unrealistic to perform a highly accurate survey with all the necessary equipment and logistics. Instead, taking slope measurement as an example, a carpenter’s level and tape are usually used. Hence, accuracy and reliability can be compromised with a limited number of samples and unpredictable human errors.

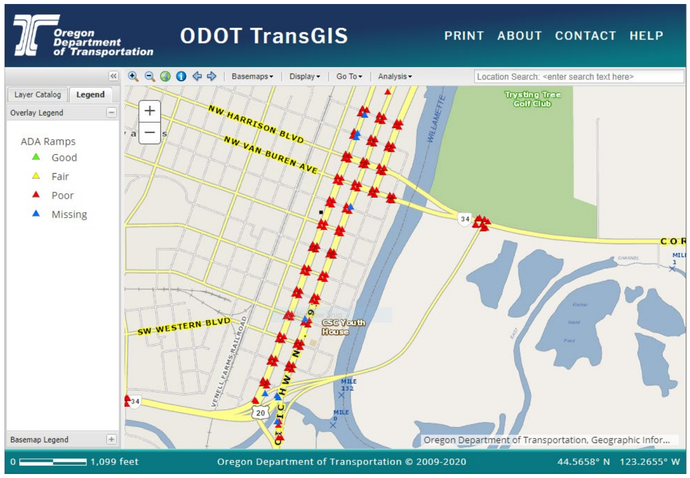


Figure 1-1. An example of the current ADA ramp inventory on Oregon state highways on ODOT TransGIS [2], where "Poor" means a curb ramp does not meet one or more ADA guidelines.

Mobile light detection and ranging (lidar) is a remote sensing technique that has been adopted by several transportation agencies to regularly collect dense 3D point cloud data with greater accuracy and efficiency for a wide variety of applications (e.g., asset management, civil design, etc.). With the detailed 3D geometric information provided by mobile lidar data, various characteristics and metrics can be extracted from a point cloud and used to examine whether a curb ramp is ADA compliant (figure 1.2). Because each point in the mobile lidar data is georeferenced, the result of the assessment can be easily added or attached to the existing inventory. However, manually processing and cleaning the mobile lidar data to use them for curb ramp assessment can be tedious and time-consuming. Additionally, a more rigorous study needs to be conducted to evaluate the effectiveness and reliability of mobile lidar-based curb ramp assessment.

Figure 1-2. An example of mobile lidar data at an intersection including a curb ramp.

CHAPTER 2 LITERATURE REVIEW

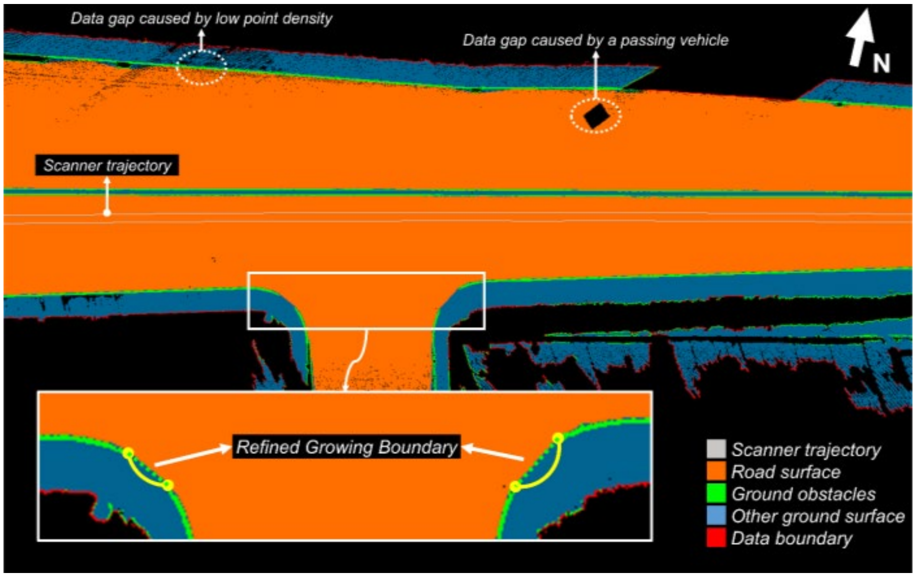
Lidar has been widely used in transportation. Olsen et al. (2013) introduced the main applications of lidar use in transportation asset management. They also pointed out that lidar has the benefit of offering faster data collection, better safety, and more convenience when the field area is hard to enter or includes potential safety hazards. However, there are a few challenges in using lidar. For example, in comparison with the high efficiency of lidar data collection, the efficiency of data processing is relatively low. There are four reasons. First, the volume of the data set is usually large, which slows down the speed of data processing. Second, most lidar data are processed manually, which can introduce human error. Third, data processing is time-consuming. Last, the process is tedious, meaning that there are many repetitive steps during data processing. Some previous studies have focused on solving these issues. This section reviews and summarizes the technologies evaluated for curb ramp localization and curb ramp assessment in previous studies.

Evaluating the ADA compliance of curb ramps can be very labor intensive and time-consuming. Because mobile lidar data can provide detailed 3D information accurately and efficiently, lidar has the potential to become a tool for automatic curb ramp evaluation. For example, Oh et.al (2018) proposed a method for automatically evaluating the ADA compliance of transportation infrastructure, including sidewalks and curb ramps, by using mobile laser scanning (MLS) and open source processing algorithms. They first acquired MLS data, and then the data were filtered. Then roads, sidewalks, and ramps were extracted by using plane normal vector information in the point cloud data. After that, key features including the slope, width, and length of each curb ramp were calculated in the point cloud data. Then they assessed sidewalk width, curb ramp cross slopes, and the connectivity with the roadway by comparing the key features from the MLS point cloud data with ground truth data that they acquired by using a measuring tape. For a selected slope, the average difference was 0.22 percent between the MLS data and ground truth data. Other methods such as a surface profiler can also be used for curb ramp assessment. Loewenherz et al. (2010) developed a method for evaluating sidewalks and curb ramps by using an Ultra-Light Inertial Profiler set on a Segway machine. This method could collect more precise data than traditional measurements. The data collected with the surface profiler were compared with ground truth data that were acquired with a smart level.

The research team performed a comprehensive review summarizing and analyzing the state of the art in object recognition, segmentation, and classification of mobile lidar data (Che et al., 2019). Many methods have been proposed and demonstrated to be able to extract or classify various objects, including roadways and curbs, that are related to curb ramps. Most recently, Romero et al., (2021) conducted a historical survey on road curb detection that reviewed and discussed a variety of road detection methods. Unfortunately, regarding curb ramps, very few studies have had success, so that gaps exist in information related to using lidar data for asset management and other applications.

Hervieu & Soheilian (2013) presented a semi-automatic approach for extracting curb ramp data based on profile analysis perpendicular to the driving direction. Although the approach has been demonstrated to be effective, such a profile-based approach can detect only curb ramps facing the lidar trajectory. Some mobile lidar systems record video logs that can be associated with a lidar point cloud. Therefore, instead of using 3D point cloud data directly, Ai & Tsai (2016) took advantage of computer vision technologies to detect curb ramps and map the detection results to the 3D point cloud with an interactive approach. Later, Ai et al. (2019) adopted the computer vision approach developed by Hara et al. (2014) to recognize curb ramps from video logs and developed a manual curb ramp measurement tool for assessing their ADA compliance. The experiment demonstrated that these approaches were effective and efficient in comparison with manual techniques, which can be tedious and time consuming. However, such approaches rely heavily on computer vision and machine learning techniques. As a result, their performance can be affected by a variety of factors, such as the number of training data sets, the quality of calibration between the cameras and lidar sensor, and other factors such as exposure settings and stitching quality. In addition, because the cameras and the lidar sensor do not necessarily capture the same objects simultaneously, a curb ramp occluded by a pedestrian or other moving objects can cause false detection results.

In the research team's previous work, a method to extract roadways and driveways was developed. In the study, Mo-Norvana segmentation (Che & Olsen, 2019) was applied to support ground filtering and the subsequent analysis. To detect the road surface, curbs and other obstacles were first extracted, followed by a simulation of a car moving on the ground. The driveways were also of interest because a vehicle would be able to gain access through them while the curb ramps would need to be eliminated (figure 2-1). By using the same concept, a similar approach should be able to extract curb ramps. However, this method was limited by the accuracy of the trajectory reconstruction, high sensitivity to noise, and certain types of mobile lidar systems.



(a) Road detection result.

(b) GIS product and accuracy assessment.

Figure 2-1. Performance of the road detection developed by the team in previous work (modified from Che et al.).

CHAPTER 3 METHODOLOGY

3.1 Overview

The research team first developed an automated workflow process to locate and orient the curb ramp from point cloud data. The process consists of three primary steps: (1) ground filtering to separate ground and non-ground points; (2) curb line detection that classifies the point cloud; and (3) curb ramp localization using the extracted curb lines. To characterize the curb ramp in terms of its running slope, cross slope, and flatness/smoothness/roughness, the research team also proposed several models that can simulate the slope measurement on a curb ramp.

In another ongoing effort by the research team, Olsen et al. (2020) is investigating the accuracy of a variety of tools for assessing the ADA compliance of curb ramps, especially for slope measurements. During the project, a couple of lidar systems (Leica ScanStation P40 and Leica BLK360) were rigorously evaluated. The results showed that the accuracy of the terrestrial lidar system (Leica Scanstation P40) is on par with that of a smart level, a tool that is widely used by contractors and inspectors to measure different slopes on a sidewalk and curb ramp. Meanwhile, the BLK360 scanner cannot be reliably used for the same purpose primarily because of the precision and accuracy of the internal compensator. For the same reason, the mobile lidar system would not be sufficiently accurate for measuring the slope of curb ramps by itself. There are other metrics such as width of a curb ramp that can be accurately measured with mobile lidar data, although this has not been thoroughly tested and documented. The accuracy of the length/width measurement is a function of lidar sensor accuracy, inertial measurement unit (IMU) accuracy, and point cloud density, which is affected by range, incidence angle, and driving speed. Therefore, this project focused only on curb ramp localization.

3.2 Ground Filtering

Ground filtering is a common step in point cloud data processing that separates ground and non-ground points. Depending on the circumstances and applications, the ground can be defined differently. For example, for mobile lidar data collected in an urban or suburban area, a lot of approaches have been developed to focus on extracting the road surface, while other approaches have a broader definition of the ground that includes the road surface, median, sidewalk, and other types of ground elements (Che et al., 2019). A curb ramp usually serves as a transitional space between the sidewalk and road surface, defined by its elevation change. As a result, in the proposed framework, a ground filter approach that could preserve the sidewalks was required because the sidewalk provides important context for identifying curb ramps. Recently, the research team proposed a novel ground filtering procedure, namely Vo-SmoG, that was demonstrated able to cope with different types of scenes and data sources (Che et al., 2021).

The Vo-SmoG starts with organizing the point cloud data through a novel voxelization approach that preserves geometric information while reducing computational complexity. Then several filters are applied to remove a variety of non-ground points, including isolated points/clusters, points that have a relatively high elevation, and points associated with a drastic slope or elevation change. Then the remaining ground candidate points are grouped into segments to complete the global refinement that further improve the result. Finally, a proximity filter is applied to map the ground candidates back to the original point cloud data and label them following the American Society for Photogrammetry and Remote Sensing (ASPRS) Lidar Data (LAS) specification. Using the mobile lidar data in a suburban scene as an example (figure 3-1, figure 3-2), the Vo-SmoG is effective and efficient at labeling not only the road as ground, but also other types of ground, including grass, gravel, sidewalks, driveways, and more. Such classified point cloud data will serve as the input for the subsequent steps.

Figure 3-1. Original mobile lidar data

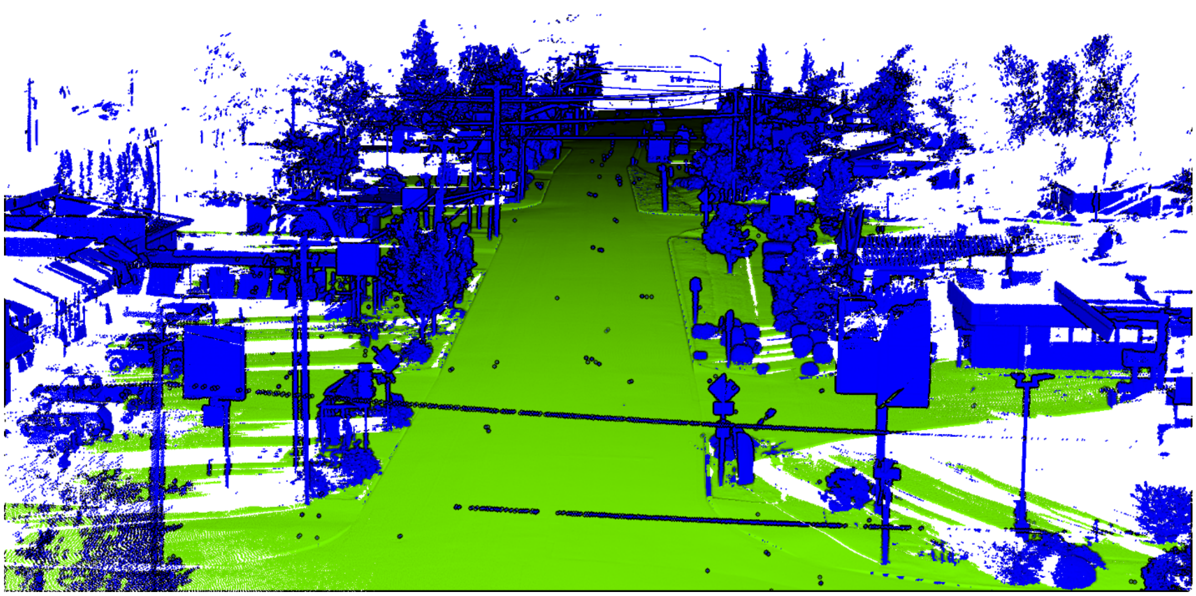


Figure 3-2. Vo-SmoG ground filtering result in which ground points are in green and other are in blue.

3.3 Curb Detection

By definition, a curb ramp is built at a certain location along the curb line to provide access from the sidewalk. Therefore, a more accurate curb detection process that provides more context can yield more robust curb ramp localization. The research team developed a curb detection approach that works with the point cloud in which the ground points have been classified (figure 3-3, figure 3-4). The proposed approach further classifies these input data by adding the class of curbs. There are four primary steps in the proposed method to detect and classify curbs: ground points refinement, curb candidate extraction, curb candidate clustering, and proximity mapping.

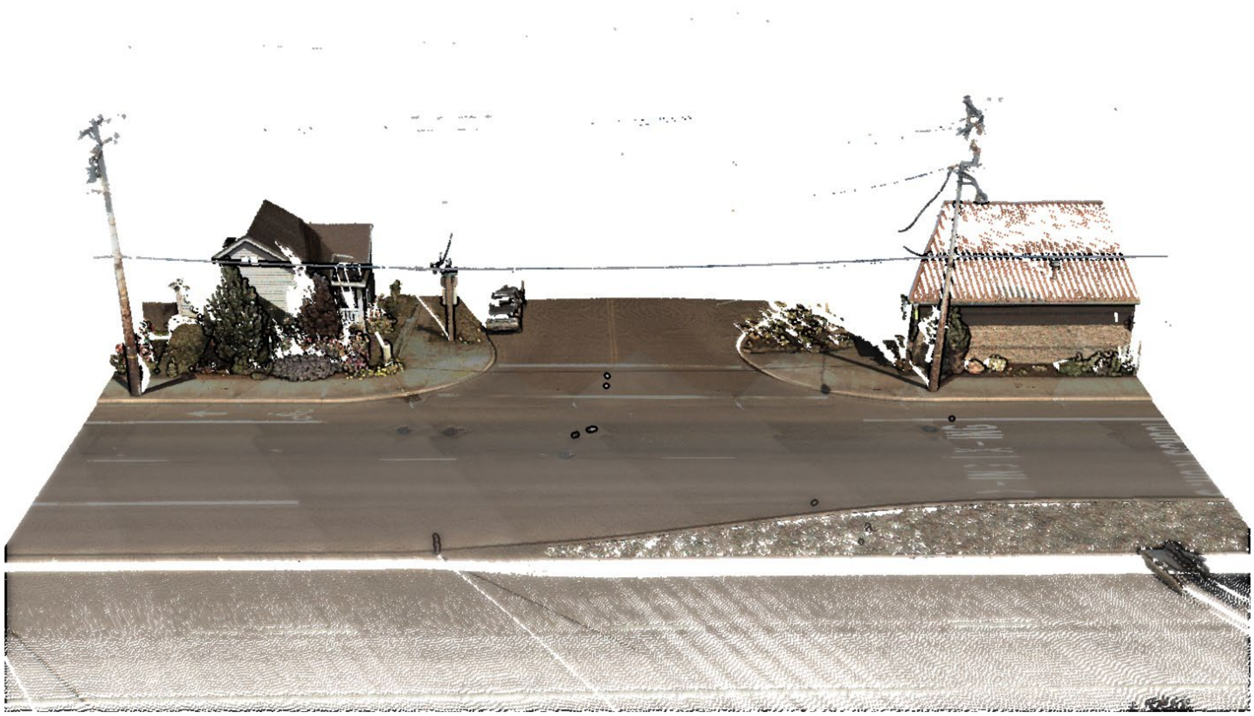


Figure 3-3. The original mobile lidar data.

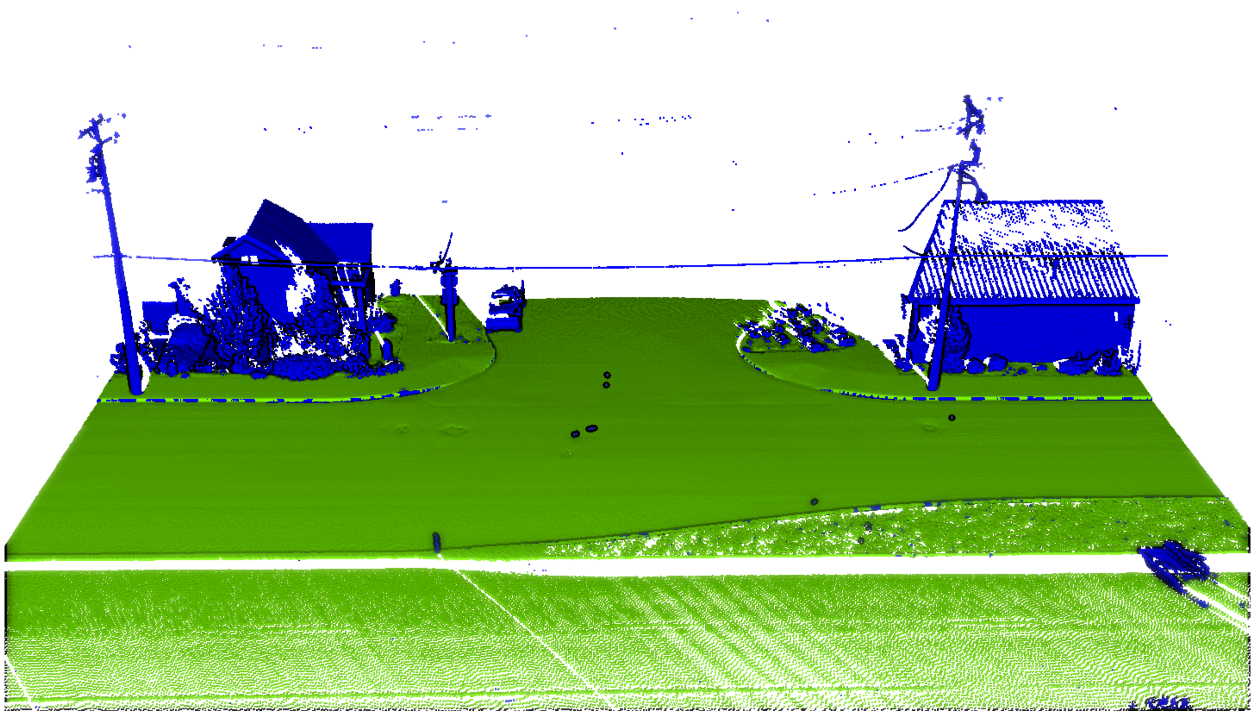


Figure 3-4. The classified point cloud from the Vo-SmoG ground filtering result.

As shown in the example of the ground filtering result (figure 3-4), without extensive parameter fine-tuning, the Vo-SmoG can provide ambiguous results at the curb face, where some points lying on the curb face are classified as ground and others are not. The definition or assumption of the ground surface applied by most, if not all, of the existing ground filtering excludes the curb face, given that it is associated with a sudden elevation change as well as a near-horizontal normal vector. To avoid extensive parameter fine-tuning of the approaches that can handle such situations such as Vo-SmoG and to tackle other, existing classified point clouds that exclude the curb face from the definition of the ground surface, the research team proposed an approach to add curb face points back to the ground points. The proposed method first voxelizes the entire classified point cloud and extracts the ground points. The voxelization process can down-sample the data and reduce the computational complexity. Notice that the proposed voxelization does not necessarily organize the data into cubes with the same dimensions in every direction. The vertical cell size is given a smaller value (e.g., 0.03 m / 1 inch) than the horizontal cell size (e.g., 0.05 m / 2 inch) so that the sampling process provides a more precise representation of the curb as a result of better alignment with the point density of the mobile lidar point cloud. Such a down-sampled point cloud is used and analyzed until the last step maps the results to the full point cloud. To include the curb face points in the ground points, each non-ground point's neighbor ground points are searched by using the voxel indices. Then each non-ground point is analyzed to examine whether its elevation is within the elevation range of the neighbor ground points. If the elevation of a non-ground point is between the maximum and minimum elevations of its neighbor ground points, then it is added to the ground points. As a result, the ground surface can include the curb face for further curb detection (figure 3-5).

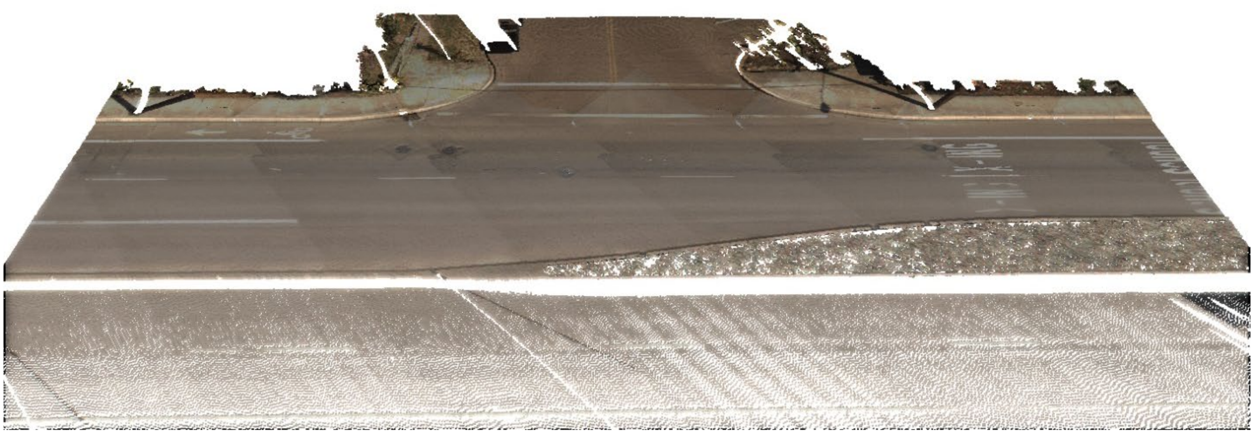


Figure 3-5. Refinement of the ground points.

To detect curb lines from the ground points from the previous step, the proposed approach applies two filters to derive the initial curb candidates. First, the normal vector at each ground point is estimated, and a threshold is applied to the z component of the normal vector to eliminate the road surface, sidewalk, and other flatter surfaces. Note that the tolerance of the normal surface or slope should be loosely assigned because of the great uncertainty at the curb regarding a sudden normal change. In this project, a maximum slope of 20 degrees (~34 percent) was used, which provided a sufficient buffer to filter the road and sidewalk surfaces while preserving the curb points. Then to further cope with false positive points in the result, a range of elevation change was used based on the general designed height of the curb, given uncertainty in the data. In this work, the height of a curb was defined to be between 0.03 m (1 inch) and 0.3 m (1 ft) to include the traffic lane separator curb that is usually significantly lower than the normal curb on the sidewalk or median (figure 3-6).

Figure 3-6. Result of the preliminary curb candidate extraction.

To this point, the proposed analysis mostly focused on local features and characteristics such as local slope and elevation change. However, relying only on local geometric attributes can lead to a lot of false positive cases for extracting curbs (figure 3.4). Therefore, the research team implemented a refinement method that clusters the curb candidate points into segments and applies a few constraints to clean up the result. To cluster the curb candidates into segments, the connected component is implemented by using the same voxelization settings that are utilized in the previous steps (figure 3-7). After the clustering, the size and linearity of each segment are examined. Most of the noise and clutter can be removed with a simple threshold for size or length for each segment to ensure that only a segment with a certain length can be considered as part of the curb lines. Then for linearity, the proposed approach utilizes principal component analysis (PCA) to calculate the linearity at each point in a segment by using the following equation:

$$Linearity = \frac{\lambda_1 + \lambda_2}{\lambda_1}$$

where λ_1 and λ_2 are the eigen vectors corresponding to the largest and second largest eigen values, respectively.

In this work, the search radius was given as 0.5 m (20 inch) empirically while the minimum average linearity was set at 0.75. The reason that the average linearity is examined instead of the overall linearity of the entire segment is that using a localized PCA calculation can better cope with the curved part of a curb line (figure 3-8).

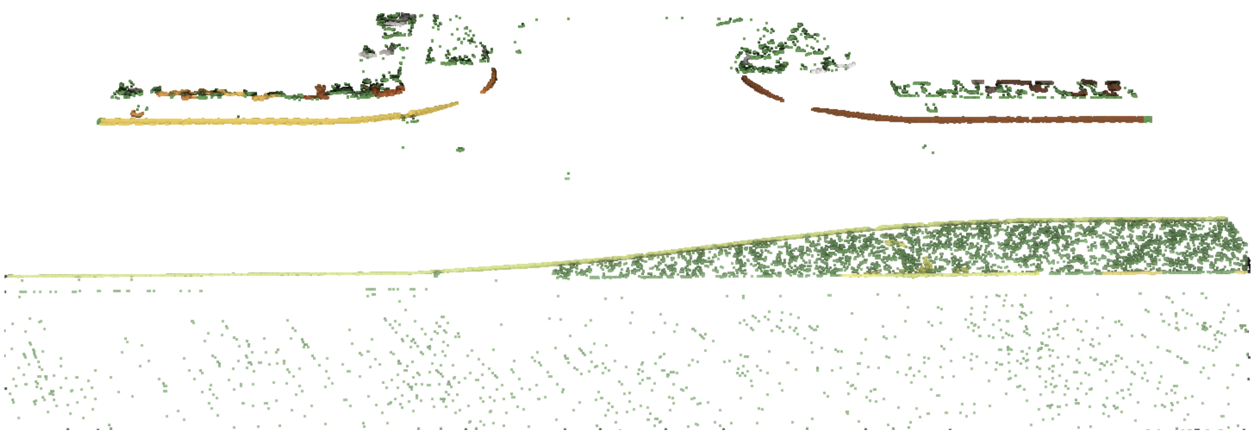


Figure 3-7. The clustering result of the curb candidates in which each color represents a segment, while green points are the small segments that do not pass the tolerance of segment size.

Figure 3-8. The result after filtering of the curb segments using the criteria of size and linearity.

The result of the clustering with additional segment/global criteria (figure 3-6) shows that the proposed approach is effective at preserving the curb lines with different shapes, heights, and lengths. However, note that the curb lines extracted at this stage are in a form of down-sampled point cloud. Although the down-sampled curb points include most of the key characteristics of the curb lines and can be used to generate vector or raster models for various applications such as asset management, such a process would inevitably cause loss of information and would be irreversible. In addition, from a data re-use and management point of view, keeping a separate sub-dataset with only one feature would substantially limit its value. Given these considerations, the research team further mapped this extraction result back to the original point cloud data with a proximity mapping process to provide maximum geometric details and context information for future re-use of the same data set for other features and applications (figure 3-9).

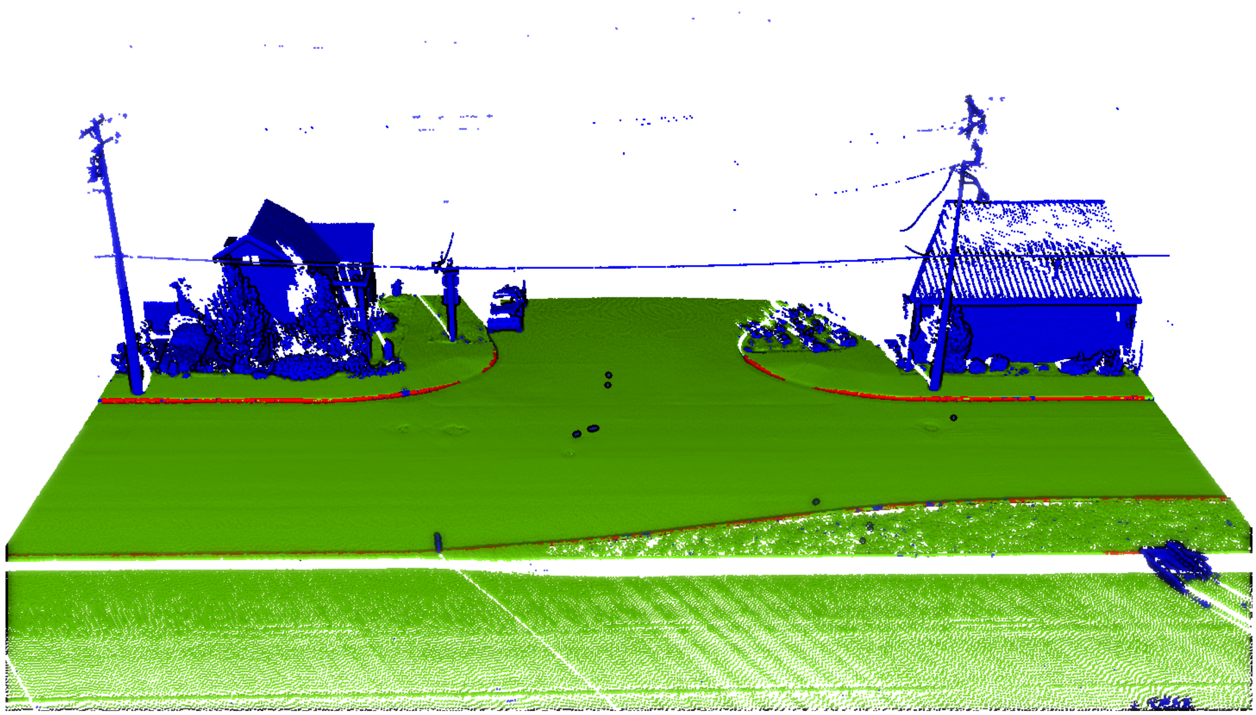


Figure 3-9. Result of proximity mapping of the curb extraction result in which the blue points represent non-ground, green represents ground, and red represents curbs.

3.4 Curb Ramp Localization

Once curb lines have been detected from the point cloud data, a curb ramp can be localized by detecting gaps between multiple curb segments with the following constraints. First, for each curb segment, other curb segments are searched within a given range of distances. Such distances can be also considered as the range of the width of a curb ramp, which was set at 1.5 m to 3.5 m in this work. The minimum width is slightly larger than that required for ADA compliance because while the curb height usually decreases gradually to the ground level and transit to the curb ramp, the proposed curb extraction based on change in elevation will not be able to capture the full extent of the curb line. On the other hand, although there is no limit to how wide a curb ramp can be, in general, curb ramps for pedestrians are significantly narrower than ramps that are part of a driveway. As a result, the maximum curb ramp width is used to distinguish curb ramps from driveways and other gaps in curb ramps that will cover most cases. Moreover, the minimum and maximum widths for curb ramps can help the algorithm cope with over-segmentation of the curb lines due to noise, occlusions, and other factors in the curb detection process.

Second, the location of the curb ramp should follow the trend of the curb lines associated with it. Thus, in the proposed algorithm, the trends of the curb lines on both sides of a curb ramp candidate are estimated by using PCA such that the deviation angle of these two curb line segments can be compared with a given threshold, which was set to be 25 degrees in this project. Once a curb ramp candidate meets the criteria of the gap width and curb line trend, then the centroid of its end points is marked as the location of the curb ramp and stored in a GIS geodatabase along with its orientation, which can potentially be used for spatial analysis and asset management. In addition, the ground points along the trend of the curb lines are labeled as curb ramps in the point cloud such that the classification can support further analysis and modeling.

CHAPTER 4 TEST RESULTS

4.1 Overview

To validate the ramp localization approach proposed in this project, the team tested the program with a data set collected by the Oregon Department of Transportation with a Leica Pegasus: Two mobile lidar system (figure 4-1 (a)). The driving speed of the data collection was about 25 mph, resulting in over 130 million points with spacings of about 0.05 m in the driving direction. Most of the area of interest along the highway was covered by two passes in the left lane of both directions. The following sections discuss evaluation and the results of the key steps of the proposed method.

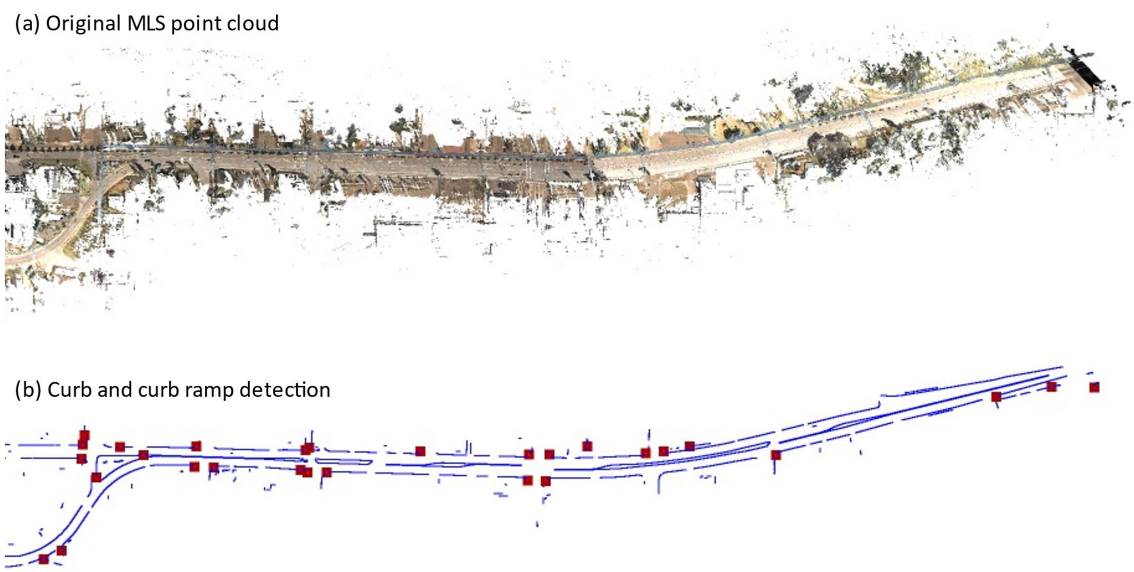


Figure 4-1. Overview of testing the mobile lidar data (a) and the curb detection (blue lines) and curb ramp (red dots) localization result (b).

4.2 Test Results

The point cloud was divided into trunks based on time stamps to make the data more manageable. The team took advantage of that data structure and performed ground filtering with

Vo-SmoG and applied the proposed curb detection approach to each trunk of data. There were two reasons for such a strategy:

(1) The georeferencing precision between multiple passes could be 0.03 to 0.05 m, resulting in artifacts and errors for the algorithms when local geometric attributes were analyzed. Processing a single pass of an area could minimize the impact of georeferencing errors in the MLS system.

(2) The computational performance was significantly higher when the data was broken into smaller pieces because of lower memory consumption and computational complexity.

The parameters for the ground filtering considered the scene type, data resolution, data accuracy, and other factors (fable 4-1), while the parameters used for curb detection were based on the discussion in the previous section (3.2.2). The height range was 0.02 to 0.30 m; the maximum road surface slope was 20 degrees; the minimum linearity was 0.75; and the minimum length of a curb segment was 1.5 m.

Once the ground surface and curb points have been identified in the MLS point cloud, the curb ramp could be extracted by searching for gaps between curb segments given the constraints of width and alignment. Because gaps between the detected curb segments could also result from occlusions due to moving objects or the limited field of view of the MLS system, the classified point clouds, including the ground and curb lines, were merged before the curb ramp localization was run to prioritize the completeness of the curb detection to achieve a better and more robust curb extraction result. Notice that after the non-ground points had been removed, the data set was reduced to only about 32 million points, which was less than one quarter of the original data. As a result, even extracting curb ramps from the merged data set would not be as time-consuming as in the ground filtering stage.

Table 4-1. Parameters used for Vo-SmoG ground filtering.

Parameter	MLS
VS_{Ground}	0.1 m
VS_{Seed}	30 m
$T_{\Delta Norm}$	15°
T_{Adjust}	0.03 m
R_{Search}	0.3 m
T_{Size}	100 voxels

As shown in the curb detection and curb ramp result (figure 4-1), the proposed method was effectively able to tackle curbs of different heights, shapes, and orientations, including the curbs of sidewalks and raised median and lane separator curbs, which are usually significantly lower than normal curbs. The output of the curb ramp localization was exported in two formats: (1) a list of the locations of the detected curb ramps and (2) a classified point cloud in which the ground points linked the curb segments associated with the detected curb ramps (figure 4-2 (a)). The first format can be directly imported into a geodatabase to store the locations and other attributes of curb ramps as a point feature. The latter format can add more information to the point cloud, which can support further classification and analysis. For example, because the curb lines are closed by the curb ramp points, the road surface is delineated by these curb lines and can be easily identified.

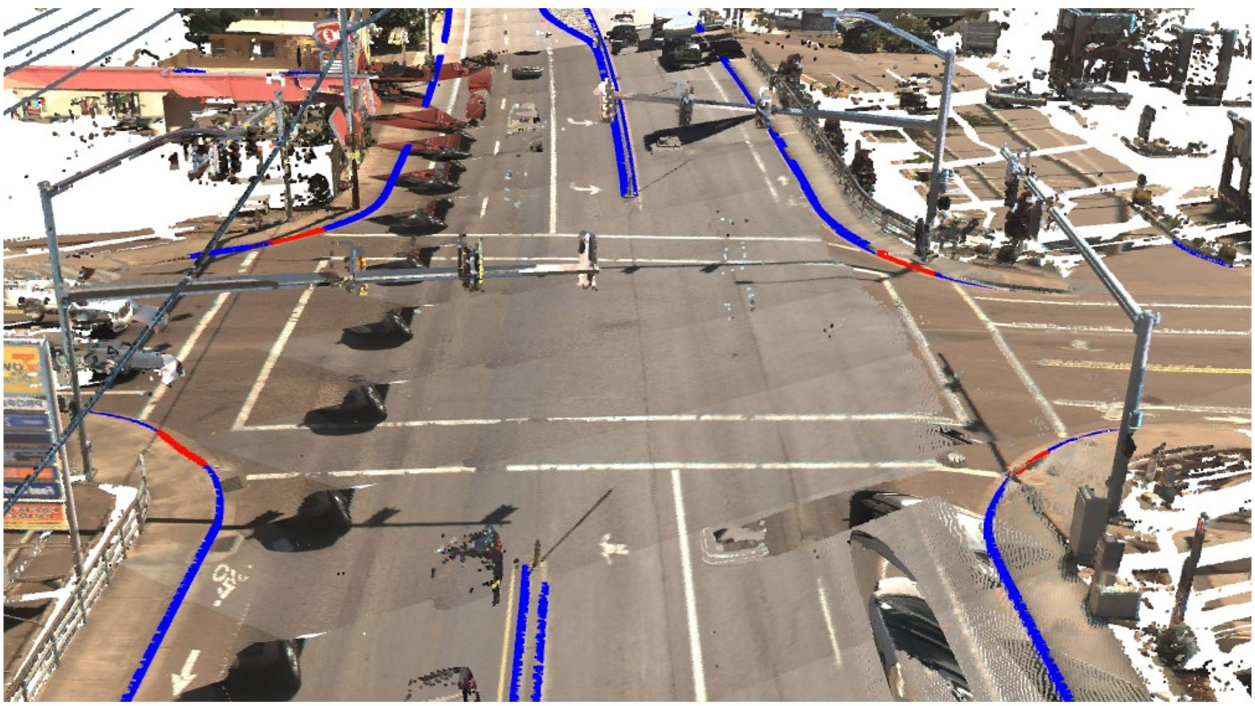
To further evaluate the performance of the curb ramp extraction, the research team manually extracted ground truth data and examined the result from the proposed workflow. In total, 29 curb ramps were spotted in the testing data; 21 were correctly detected and eight were falsely identified. In addition, eight curb ramps were missed by the program. The recall, precision, and F1-scores were all 72.4 percent. It is worth pointing out that none of the driveways in the area was mislabeled as a curb ramp, which demonstrates the effectiveness of the criteria for the width range built into the program.

It is also worth noting that errors were seen in the results, including both false negatives (e.g., the missing curb ramp in figure 4-2 (b)) and false positives (e.g., the misclassified curb ramp seen in figure 4-2 (c)). Most false identifications of curb ramps were caused by errors in curb detection propagated to the curb ramp extraction analysis.

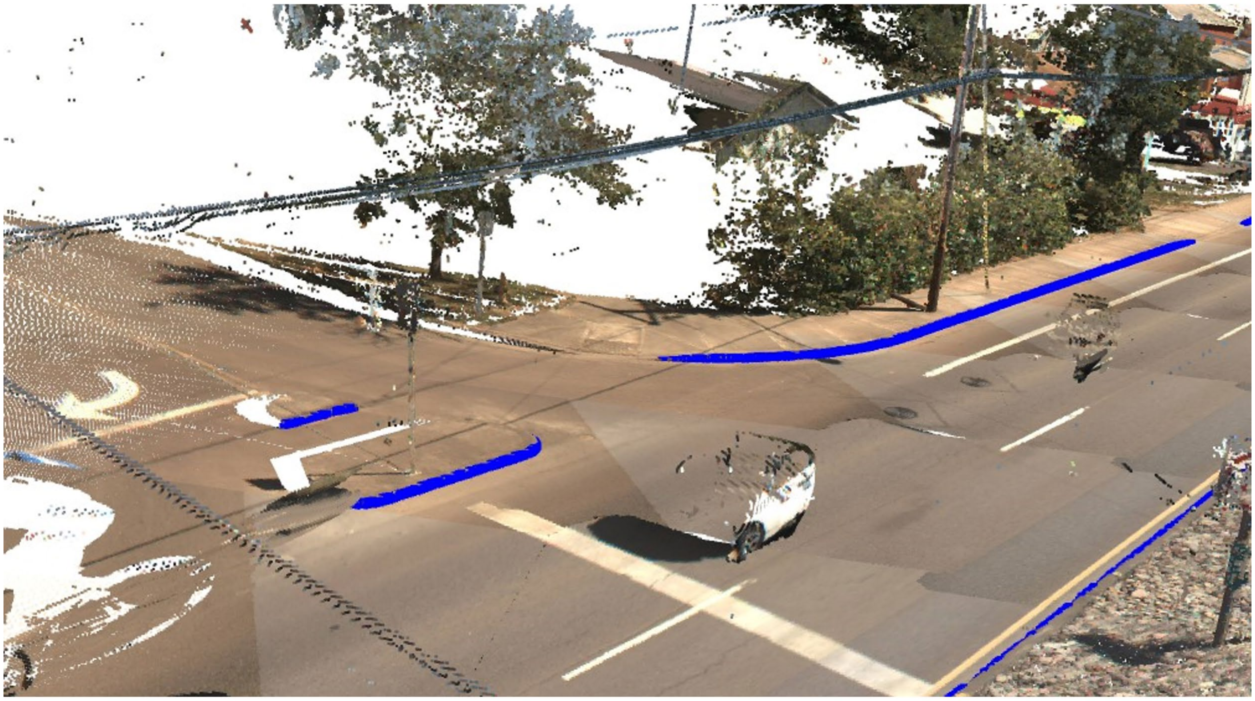
As the point density on the curb face decreased with the increasing ranges and angles of incidence, it became more challenging to detect curb ramps in such areas. Moreover, the mobile lidar system used in the test was equipped with a single 2D profiler mounted at a 30-degree angle in relation to the driving direction to prioritize the surface facing the vehicle on the right side. As a result, curb faces with a certain orientation (along the driving direction on the left or opposite of the driving direction on the right side) were poorly covered by the system, which further caused the errors in curb detection and curb ramp localization (e.g., figure 4-2 (b)). Fortunately, this challenge can potentially be overcome in two ways: 1) add a second profiler or adjust the angle of the profiler to improve the coverage of the curbs and curb ramps in each individual pass and 2) cover each leg of the intersection to capture the curb lines in each direction.

In addition to curbs, there are other common objects in a street scene that are similar to curbs in terms of their geometric characteristics, such as stair steps and parking blocks (Figure 4-

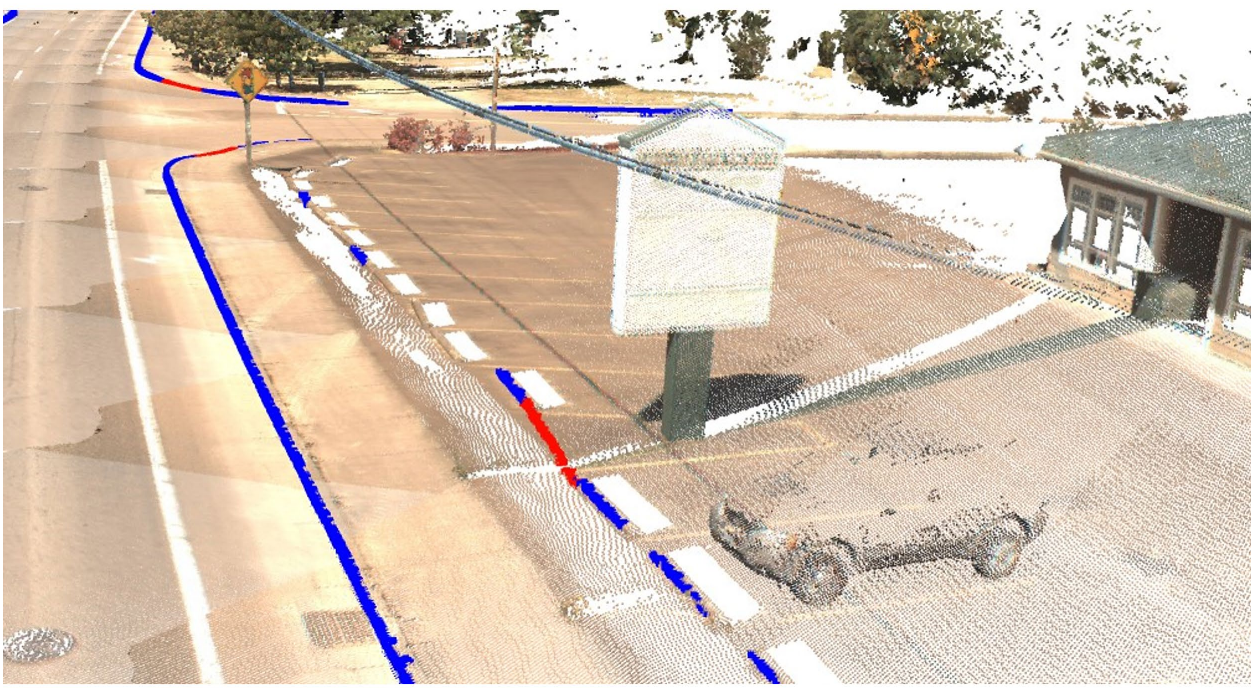
2 (c)). In most cases, these objects are significantly shorter than curb lines. However, as discussed in the previous section, the curb line is not necessarily covered to its full or a substantial extent. Therefore, the potential solution to cope with such issues would be to consider more context and semantic information. For example, given the nature of mobile lidar system and the asset of interest, the curbs along the road surface should be distinguished from others. In the testing results, there were no false positives showing on the road surface. Therefore, if the road surface can be classified in the point cloud, then curb-like objects away from the road can be easily identified and eliminated, yielding a more accurate curb ramp localization result.



(a) An intersection where all four curb ramps are correctly identified.



(b) A missing curb ramp due to incomplete curb detection caused by low point density.



(c) A falsely identified curb ramp due to parking blocks detected as curbs.

Figure 4-2. Examples of the performance of the proposed approach in which blue and red points represent curbs and curb ramps, respectively.

CHAPTER 5 CONCLUSIONS

This project proposed an automatic curb ramp localization approach for mobile lidar data. The proposed approach consists of three steps: ground filtering, curb detection, and curb ramp localization. The research team adopted Vo-SmoG ground filtering from the team's previous work. The ground surface is modeled, and the curb line is detected on the basis of its elevation change and linearity. The the gap between two curb lines becomes a candidate curb ramp and is further screened on the basis of the width and alignment of the associated curb lines. The proposed approach was demonstrated to be effective and efficient through a test on a large mobile lidar data set. The recall, precision, and F-1 scores were 72.4 percent in terms of identifying the curb ramps from the point cloud data. The errors were further analyzed and are discussed. Given that the proposed approach results in a classified point cloud, in the future, the research team will leverage the approach to further classify and characterize more features for asset management and other applications.

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