Urban accessibility diagnosis from mobile laser scanning data

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November 2018

1 Introduction

As a part of Cap Digital Business Cluster TerraMobilita project:"3D mapping of roads and urban public space, accessibility and soft-mobility", the work of Andres Serna et al. [1] from Centre de Morphologie Mathematique of MINES ParisTech mainly presents an approach for automatic analysis of urban soft-accessibility using mobile laser scanning (MLS) point cloud.

Their work in this paper mainly uses gray-scale image processing techniques, such as morphological operations, geodesic measurement, and curb recognition. By processing and analyzing the range image constructed from MLS point cloud, Andres Serna et al. realized the segmentation of ground, facades and objects, and then detected and reconnected curbs of sidewalks, classified into two classes: wheelchair-accessible and wheelchair-inaccessible. The itinerary planing part is not included in this paper.

In this report, a brief introduction of the methodology will firstly be presented, followed by some comments and suggestions of potential improvements. The second part of this report will give a more detailed explanation of the realization of the process based on my efforts in reconstructing the method mentioned in the paper. In fact, most of the process mentioned are realized with Python language by myself, with some changes on details. A test on a MLS data set of Paris (which is not the same one used in the paper) proves the correctness, but also shows some limits.

2 Methodology presented in the Paper

2.1 General introduction

We can firstly cite a paragraph of the paper to summarize the methodology of this work:
First, input point cloud in mapped to range images. Second, the image is interpolated in order to avoid connectivity problems and the quasi-flat zones algorithm is used to segment the ground (road+sidewalk). Third, facades and objects are extracted using morphological transformations and the obstacle map is defined. Then, curb candidates are selected using height and elongation criteria, and close curbs are reconnected using Bezier curves. Curbs accessibility is defined according to international standards. Finally, the obstacle map is used to define adaptive itineraries taking into account the path width such that a wheelchair can pass.

2.2 Work flow

The work flow consists:
- Projection to range images
- Image interpolation
- Ground segmentation
- Facade segmentation
- Object segmentation
- Curb detection
- Curb reconnection
- Accessibility analysis

2.2.1 Projection to range images

3D point clouds are firstly projected to range image because they are convenient structures to visualize and process data. Two kind of range images are defined:
- *Maximal range image*: stores the maximal depth among all projected points on the same pixel.
- *Minimal range image*: stores the minimal depth among all projected points on the same pixel.

Spatial pixel size should be carefully chosen according to point cloud resolution in order neither to generate holes nor to loose too much information. In the paper, a pixel corresponds to a square of 10 cm side.

2.2.2 Image interpolation

The aim of this operation is to fill holes caused by occlusions and missing scan lines. A morphological interpolation based on filling holes was used after defining artificially some boundaries inside the image where the points are too sparse.

2.2.3 Ground segmentation

For ground segmentation, the λ-flat zones labeling algorithm was applied, where two neighboring pixels belong to the same quasi-flat zone if their height is smaller than or equal to a given λ value. The ground is recognized as the largest λ-flat zone on the range image with $\lambda = 20cm$.

2.2.4 Facade segmentation

Once the ground is extracted, all remaining structures are considered as facades and objects. Some special proprieties of the data set was used to help the segmentation of facade. Generally speaking, the highest points are labeled as facade marker candidate. Then the maximal geodesic elongation is used to leave only thread-like candidates.

2.2.5 Object segmentation

Urban objects are assumed as bumps on the ground in the range image. They are extracted using the top-hat transformation by filling holes, which is defined as

$$F_{\text{top-hat by filling holes}}(x) = F_{fill}(x) - x \tag{1}$$

2.2.6 Curb detection

Firstly, the morphological external gradient is computed using a hexagonal structuring element of size 0.1m. Regions with range changes between 3cm and 20cm are considered as curb candidates. Then, a minimum elongation $E_{min} = 10$ is experimentally defined in order to accept curbs.

2.2.7 Curb reconnection

In order to overcome the lack of connectivity between curbs due to access ramps, occlusions, missing scan lines and acquisition problems, a reconnection strategy based on quadratic Bézier curves is proposed. Two curbs closer than a threshold $d_{min} = 5m$ are reconnected tracing a Bézier curb between their geodesic extremities. A quadratic Bézier curves follows the following form:

$$B(t) = (1-t)^2 P_0 + 2(1-t)tP_1 + t^2 P_2, \forall t \in [0, 1] \tag{2}$$

Here, P_0 and P_2 correspond to the geodesic extremities of the two curbs, and P_1 is in the middle of them if the two curbs are co-linear and is the intersection of the two projection lines if they are not co-linear.

2.3 Comments

This procedure can analyze Mobile Scanning Laser data of a city and segment facades, ground, obstacles, and then detect sidewalks and judge whether the sidewalk is accessible with wheelchair. In stead of dealing directly with 3D point cloud, this work proposes a method of projecting the point cloud on 2D range images, so that we could manipulate gray-level images which are much less heavy an have more mature processing methods. The authors shows their mature ability in applying morphological operations and in using them to solve difficult problems with reasonable time. Except the part of image interpolation (section 2.2.2), where we need to define artificially some boundaries of blocks, most parts of this procedure is automatic. The result shown in the paper indicates robustness and reliability in the testing data.

However, in my opinion, there are some points that could be reconsidered:

Firstly, some of the parameters should be chosen very carefully depending on the test data. During the reconnection of curbs, if the threshold that we use to judge if two curbs should be reconnected is smaller than width of the road, the curbs that belong to opposite sides of the road could be wrongly reconnected. Concerning this point, maybe we could add a criteria to separate false alarms: if a reconnection curb is far away from the facade, eliminate it.

Secondly, if there are parking cars on the road, the sidewalks behind the cars could not be detected by Laser scanning, but the algorithm didn't take any measures to try to complete the hidden sidewalks.

3 Realization of Algorithm

3.1 General introduction

In order to better understand the method in the paper, I tried to fully reconstruct all the algorithms used by the team of Andres, with some methods changed and some details completed. However, the data set used by the team of Andres is not available from internet. Therefore, the data set I used

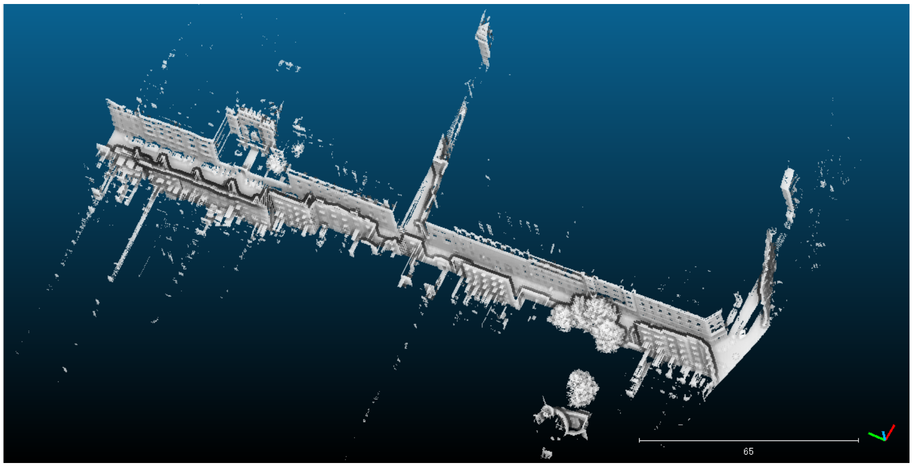

Figure 1: Dataset from "IQmulus TerraMobilita Contest"[2]

in this project is found from the internet "IQmulus & TerraMobilita Contest"[2], which contains a street section of Paris of 200 m long (12 million points).

The work flow of my algorithm can be resumed as:

0: Pre-processing of data

0.1: Load Original Point Cloud

0.2: Grid Sub-sampling

0.3: Data cleaning

0.3.1: Eliminate isolated points

0.3.2: Eliminate too high points

0.3.3: Set the lowest level of points

1: Load pre-processed Point Cloud

2: Transform the 3D points into range image

3: Fill the holes with morphological transformation

4: Segmentation of ground

5: Segmentation of facades

6: Segmentation of object

7: Segmentation of curbs

7.1: Find original curbs

7.2: Connect directly the curbs too closed

7.3: Use bézier curbs to connect curbs not that closed

8: Color the cloud points

3.2 Pre-processing of data

The original data set is relatively heavy for the following operations. Besides, due to the propriety of laser scanning technique, there are many points that are far away from the road which could unreasonably enlarge the size of range image that we will introduce. So at the very beginning we sub-sample the data by grid of $5cm \times 5cm \times 5cm$, eliminate the isolated points with less than 10 neighbors in a sphere of $1m$. The neighbor searching technique is based on KD-trees.

What's more, the data that I download from the internet can reach some points really high, which is different from the data used in the paper (where only structures lower than $2.5m$ were captured). So, the points higher than $5m$ are eliminated.

These operations are not necessary but could accelerate the following calculations and could limit the range of point cloud in order to get better pictures. Besides, while computing the max range image (as described in section 2.2.1), eliminating the points higher than $5m$ could help to eliminate the crowns of big trees.

3.3 Transform the 3D points into range image

First, we transform the 3D points into range image, as described in the paper, we also create two range image: *maximum range image* and minimum range image. Each pixel in range images represents a square of $0.1m \times 0.1m$.

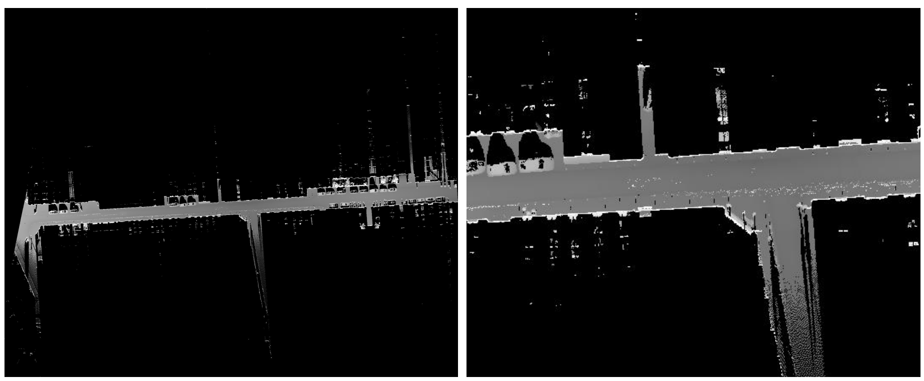

Figure 2: Max range image (Left: full size, Right: Zoom) (The brighter, the higher.)

3.4 Fill the holes with morphological transformation

Naturally, due to missing Laser Scanning points, the two range images contain some holes. In this step, my aim is to fill these holes. The pixel values in the holes are aimed to be **the lowest value on the boundary of the hole**.

The morphological reconstruction operation [3] allow us to achieve this goal without parameters. Different from the method described in the paper, I didn't create any artificial boundaries. Instead, I modified the way to define seed functions to be used in morphological reconstruction by erosion: the mask functions are the original range images with holes, while the seed functions are defined as follows:

$$f_{seed}(x, y) = \begin{cases} 0, & \text{if } (x, y) \text{ is on boundaries,} \\ 255, & \text{if } f_{mask} \text{ has no value on } (x, y), \\ f_{mask}(x, y), & \text{otherwise.} \end{cases} \tag{3}$$

With the seed(marker) function and mask function defined above, the reconstruction operation works as explained by figure 3.

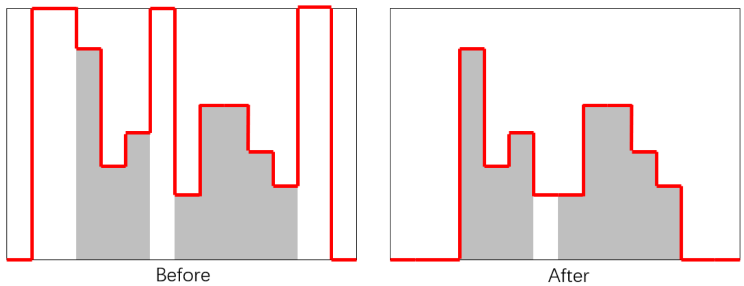

Figure 3: Morphological reconstruction by erosion (Left: in red: f_{seed}, in gray: f_{mask}; Right: in red: reconstructed function)

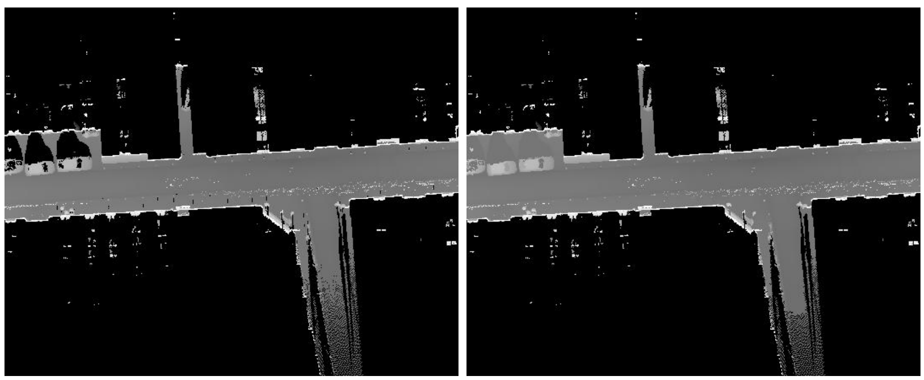

Figure 4: Fill the holes (Left: max range image before hole filling ; Right: After hole filling.)

3.5 Segmentation of ground, facades and objects

Based on the two range images, I then implemented the algorithms for the segmentation of ground, facades and objects.

Using the min range image, the ground was identified using λ-flat zone method, where two neighboring pixels belong to the same quasi-flat zone if their height is smaller than or equal to a given λ value. The ground is recognized as the largest λ-flat zone on the range image with $\lambda = 20cm$.

The facades are found following two steps: firstly, every pixels on the max range image that represents a height higher than $4m$ are labeled as facade candidates; secondly, for each set X of connected facade candidates, the geodesic elongation $E(X)$ was computed, and those sets with $E(X) > 5$ are selected as facades (in this way, we only keep the elongated structures). Here, $E(X)$ is defined as :

$$E(X) = \frac{\pi L^2(X)}{4S(X)} \tag{4}$$

where $L(X)$ is the geodesic measurement of set X and $S(X)$ is it's area. (Technically, the computation of geodesic measurement is simil) Breadth First Search (BFS) algorithm.r Finally, the obar tojects are defined as holes on the ground, which can be easily labeled by doing a subtraction

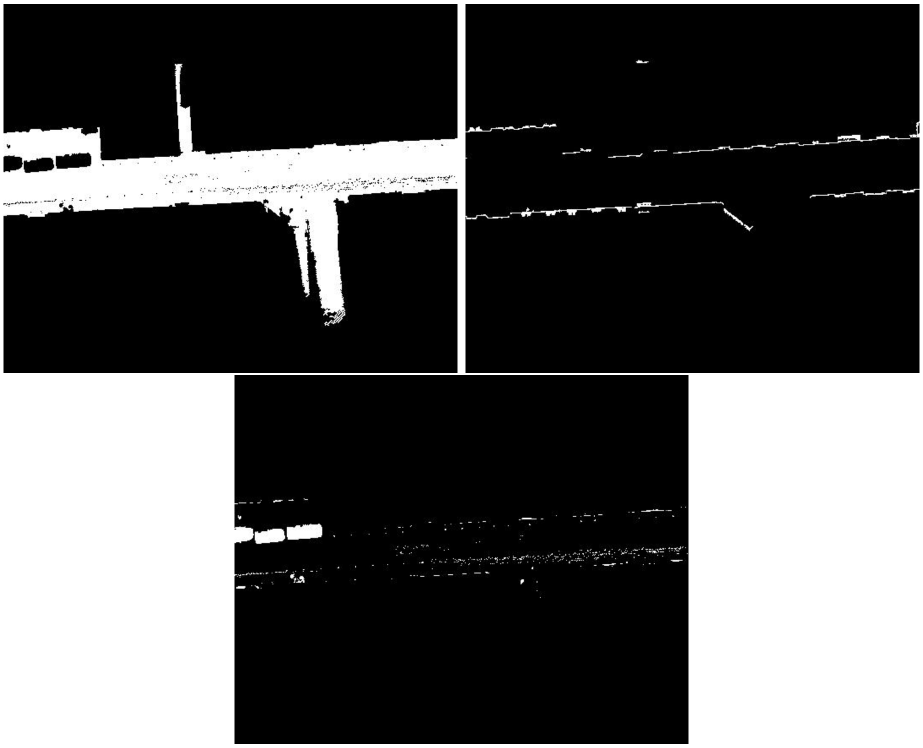

Figure 5: Segmentation of ground (top left), facades (top right) and objects (bottom). There are some noise on segmentation of objects.

between ground and it's morphological reconstruction (top-hat operation by filling holes).

3.6 Segmentation of curbs and curb reconnection

In this part, we aimed to identify the gaps between sidewalks and road and classify them into two classes: *wheelchair-accessible* and *wheelchair-inaccessible.*

3.6.1 Find curbs

The curbs candidates are the pixels where there are range changes between $4cm$ and $20cm$. We use morphological external gradient, which is the difference between original image and it's dilation, to represent range changes. The kernel (structural element) chosen for external gradient is a 3×3 square kernel. Then, as is used for facades segmentation, the control on geodesic elongation allows us to select those elongated structures. One can find the results of original curb segmentation in Figure 6.

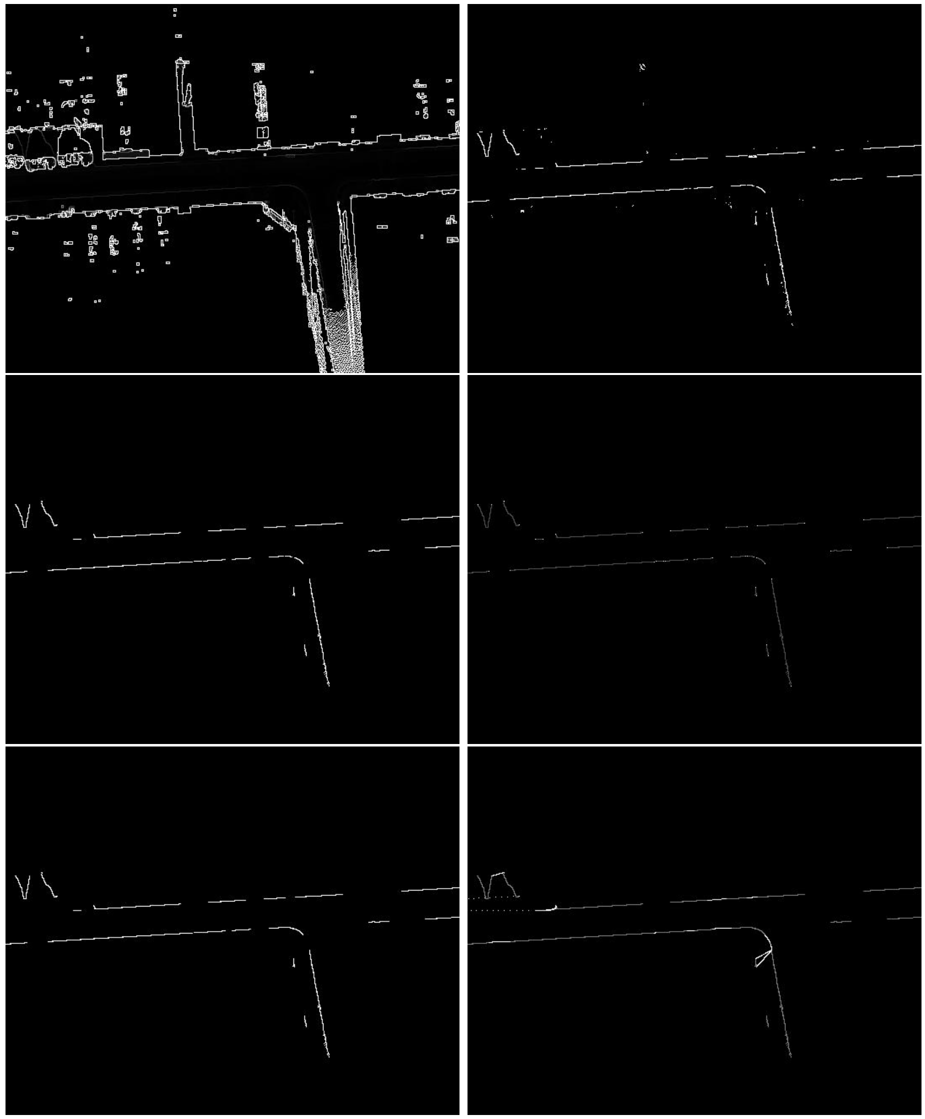

Figure 6: Top left: External Gradient; Top right: Curb candidates;
Middle left: Initial curbs; Middle right: Endpoints;
Bottom left: Initially reconnected curbs; Bottom right: Curbs reconnceted with bézier curves

3.6.2 Augment the connectivity

The originally selected curbs are very poorly connected due to gradient computation. Before reconnecting them with bézier curves, we need to firstly reconnect the curbs that are isolated because of numerical problems.

In order to reconnect the curbs that are really closed to each other, we need to find the two endpoints for each curve. Practically, for each set of curve, the two endpoints are found as **the two pixels of which the geodesic distance reaches the geodesic measurement of the curve**, which is to say that the two endpoints have the largest geodesic distance in the curve. Then we reconnect the endpoints of different curves with a distance less than $0.4m$ with straight segments.

3.6.3 Use bézier curves to reconnect curbs

As described in the paper, we reconnect curbs with a distance between $0.4m$ and $3m$ with bézier curves by adding a reference point. After identified the couples of endpoints $(P_0, P_2)_i$, there are three cases to discuss. If the two curbs to connected are co-linear or quasi-co-linear, the third point P_1 will be the middle of the two endpoints to reconnect. If the two curbs forms a rather big angle, the third point P_1 is on the intersection point of the two projection lines. If the two curbs are parallel or quasi-parallel but the distance between the two curbs are relatively large, we consider the two endpoints to be on the opposite side of the road and won't reconnect them.

A little detail to emphasize is that PCA (Principle Component Analysis) is used to find the direction of projection lines. After doing PCA on each endpoint, we can associate each endpoint with a normalized direction vector (a, b) verifying $\sqrt{a^2 + b^2} = 1$.

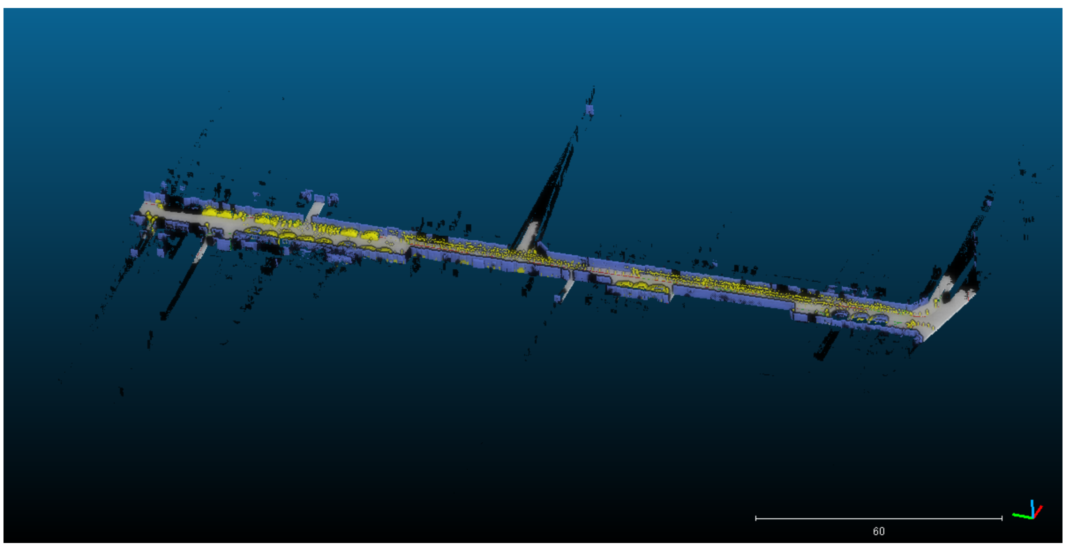

Figure 7: Results of segmentation in color (Gray: ground; Blue: facades; Yellow: objects; Red: wheelchair non-accessible curbs; Green: wheelchair accessible curbs)

4 Results and Conclusion

This procedure is fully automatic, and gives good results in segmentation of ground, facades and objects. However, some problems could be found during the segmentation of curbs. For example, the deceleration strips could be classified as curbs because they are really difficult to be distinguished with a threshold. Besides, the missing Laser Scanning Points and hidden zones could raise many false alarms when classifying and trying to reconnect curbs (Figure 8), and some of the choice of parameters depend strongly on the database.

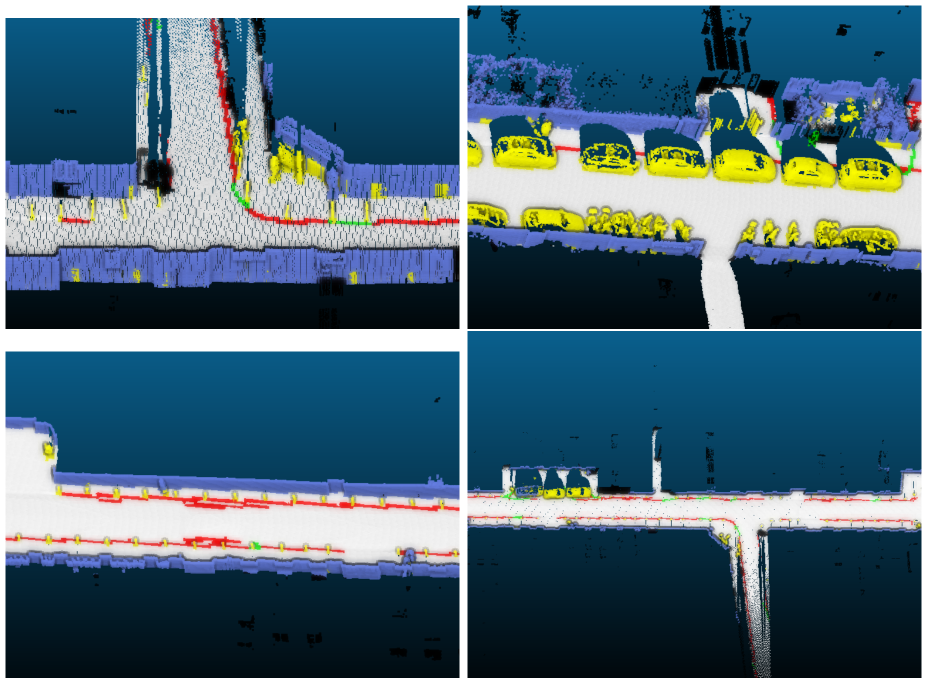

Figure 8: Some parts of the colored point cloud. (the image on top right shows some false alarms due to missing scanning points and the image on bottom left shows a wrongly segmented deceleration strip)

Concerning computation time, to deal with the data set of 12 million points, if we skip to procedure of eliminating isolated points, the total procedure takes less than 2 minutes. However, the step of eliminating isolated points could take as long as 5 hours even using KD trees while counting number of neighbors of a point.

Generally speaking, the method in the paper gives me many fresh ideas on how to deal with gray-level images. Some method, such as morphological reconstruction, opening/closing, erosion/dilation, morphological gradient, PCA, λ-flat zone method and geodesic measurement would be really useful for me in the future.

Passing from 3D point cloud to range images can gain us many advantages, such as much less computation time and a large amount of mature methods based on gray-level images. However, inevitably, we lose information during the projection. So, reasonably return to 3D point cloud may help us get better results.

References

[1] Andrés Serna and Beatriz Marcotegui. Urban accessibility diagnosis from mobile laser scanning data. *ISPRS Journal of Photogrammetry and Remote Sensing*, 2013.

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[3] Luc Vincent. Morphological grayscale reconstruction in image analysis: Applications and efficient algorithms. *IEEE Transactions on Image Processing*, 2:pp.176–201, 1993.