An Adaptive Down-sampling Strategy for Efficient Point Cloud Segmentation

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Abstract

3D modelling of objects can be achieved through either optical imagery or laser scanners. For optical imagery, advanced matching techniques can generate dense point clouds from multiple overlapping images. On the other hand, laser scanners can directly provide precise and reliable 3D point clouds along scanned objects. Derived point clouds from laser scanners and dense-matching techniques usually include excessive number of points. Processing (e.g., segmentation of planar and linear/cylindrical features) such huge number of points is computationally expensive and might not be necessary. For example, to segment planar regions, we can obtain reliable segmentation results while using fewer points in areas with dense point distribution. Therefore, down-sampling (i.e., thinning) the original point cloud is a good strategy to increase the efficiency of the data processing stage. However, inappropriate down-sampling might compromise the segmentation results.

This paper introduces an adaptive down-sampling procedure that only removes redundant points. More specifically, in areas with high point density, more points are removed while the majority of points will be maintained in areas with sparse points. The paper also presents segmentation results for original, randomly/uniformly down-sampled, point-spacing-based down-sampled, and adaptively down-sampled point clouds while commenting on the computational performance and segmentation quality for these scenarios. The results demonstrate that the adaptive down-sampling represents the best balance between maintaining inherent details and speeding-up the segmentation process.

Keywords: Adaptive Down-sampling, Point Density, Segmentation, Quality Control

1. Introduction

Three dimensional modelling of our environment is important for many applications, such as digital building model generation, urban planning, as-built mapping of industrial sites, cultural heritage documentation, and change detection. The main tools for acquiring the necessary data for 3D object reconstruction and modeling are optical imagery and laser scanners. Laser scanners can directly deliver precise point clouds along scanned objects with high density. Using optical imagery, one can also generate point clouds through the matching of conjugate features in overlapping images. The derived point clouds from either approach can then undergo processing techniques for 3D modeling of objects within the sensors' field of view.

Based on the utilized platform, laser scanners can be categorized into airborne laser scanners (ALS), terrestrial laser scanners (TLS), and mobile terrestrial laser scanners (MTLS). ALS units are mainly used for the generation of digital elevation models (e.g., digital surface models – DSM – and digital terrain models - DM) as well as digital building models (DBM). Acquired point density from ALS, which is usually in the range of 1 to 40 pts/m^2 (Hyyppä et al., 2009) is suitable for building roof extraction and DTM generation. For example, Habib et al. (2010) used ALS data with point density of roughly 1.5 pts/m^2 for terrain and off-terrain classification of the point clouds as well as the extraction of roof patches. The roof boundaries are then refined with the help of imagery for accurate DBM reconstruction. Kraus and Pfeifer (2001) worked on eliminating off-terrain objects to generate high quality DTMs. Due to the nature of the data acquisition scenario, ALS data cannot provide the necessary details for the extraction of specific objects such as building facades, light poles, trees, and fences. Recent developments in laser scanning and geo-referencing technologies are allowing for the acquisition of point clouds with high point density from other platforms in a short time (e.g., MTLS and TLS systems). Such systems deliver point clouds that can be used of the extraction of objects that could not be derived from ALS data as well as indoor modeling. Valero et al. (2012) used TLS to generate indoor building models through a space-discretization segmenting procedure. Yang et al. (2012) used

MTLS to generate geo-referenced feature imagery for classifying and extracting building facades and trees through shape constrains. Based on the above discussion, one can see that current research and technological advances clearly demonstrate that LiDAR systems onboard different platforms can be used for the acquisition of point clouds for various 3D modeling applications.

Optical imagery, on the other hand, can generate 3D models and point clouds by matching conjugate features in overlapping images. Through feature-based matching, 3D points and linear features can be derived from imagery (Baillard et al., 1999). However, feature-based image matching is not capable of reconstructing a 3D model with high level of detail. In order to get more details, pixel-wise matching – dense-matching – techniques could be implemented. Haala (2013) has shown that dense matching and current software tools are capable of generating large scale landscape digital surface models from airborne imagery.

Derived point clouds from TLS, MTLS, and image-based dense-matching techniques usually include excessive number of points. Processing (e.g., segmentation of planar and linear/cylindrical features) such huge dataset is quite time-consuming and might not be necessary. For example, to segment planar regions, we can obtain reliable segmentation while using fewer points in areas with dense point distribution. Therefore, available software tools for point cloud processing (e.g., "Cloudcompare" (2011)) have down-sampling functions to thin large datasets. The research community has been also working on developing alternative strategies for point cloud down-sampling. For example, Puttonen et al. (2013) proposed two methods for down-sampling point clouds according to the point-to-scanner distance. However, none of the above techniques consider the point distribution along physical surfaces during the down-sampling process. For laser scanners, the point density depends on the distance between the scanner and the scanned objects. For image-based point clouds, on the other hand, the point density depends on the texture of visible surfaces (Mikolajczyk et al., 2005) and the extent of occluded areas.

An optimum down-sampling should consider the varying point density. In this paper, we introduce an adaptive down-sampling procedure (Al-Durgham et al. 2014) that only removes redundant points as defined by estimated and desired point density values. More specifically, more points are removed in areas with high point density while the majority of points in areas with less point density are maintained. Furthermore, we present segmentation results from the original, randomly/uniformly down-sampled, point-spacing-based down-sampled, and adaptive down-sampled point clouds while commenting on the computational performance and segmentation quality in these scenarios. The paper finally makes some conclusions and recommendations for future work.

2. Scheme

In this section, we introduce the strategy for the adaptive down-sampling which will be applied prior to point cloud segmentation for the extraction of planar and linear/cylindrical features. Then, quality control measures are utilized for improving the segmentation results, which are finally evaluated to investigate the impact of different down-sampling procedures. The flowchart for the down-sampling and point cloud segmentation is shown in Figure 1.

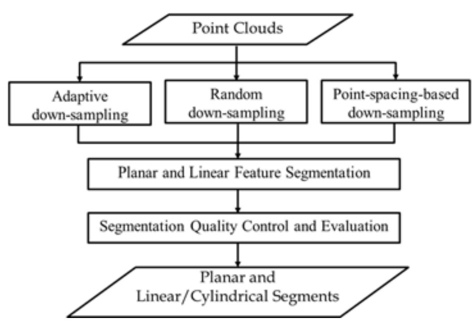


Figure 1. Flowchart of the down-sampling, segmentation, and testing strategy

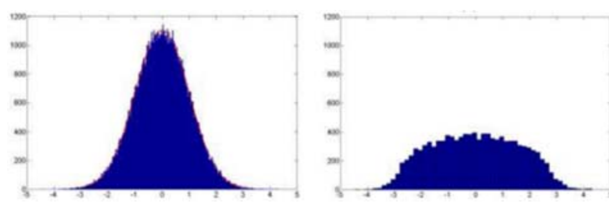
2.1. Adaptive Down-sampling

For reducing the size of a given point cloud, random down-sampling is the most commonly used approach. Such an approach removes points using a specific down-sampling rate throughout the entire area. This strategy would lead to loss of details in low-density areas. Therefore, to avoid compromising post-processing activities while enhancing their execution time, an adaptive down-sampling should be used to keep points in low-density areas and remove redundant points in high-density areas. Therefore, the first step of the proposed strategy is to evaluate the point density at the individual points as represented by their local neighborhoods. In this paper, we implemented the proposed methodology in Zahra and Habib (2013) for local point density estimation. Then, the introduced adaptive down-sampling in Al-Durgham (2014) is carried out by specifying a desired point density while using the probability-based test in Equation 1.

$$\delta = \frac{t}{d_i} = \begin{cases} \geq r & , use \\ else & , ignore \end{cases} \tag{1}$$

Where,
t is the desired point density in pts/m^2,
d_i is the local point density at the ith point local neighborhood in pts/m^2, and
r is a random number that is picked from a uniform distribution in the range [0, 1].

According to Equation 1, in areas where the point density (d_i) is less than the desired point density (t), the test value (δ) will be larger than 1, which in turn will be larger than any randomly selected value (r) from a uniform distribution in the range [0, 1]. Therefore, those points will be maintained in the down-sampled dataset. Alternatively, in areas where the point density (d_i) is larger than the desired point density (t), the test value (δ) will be less than 1. In a given neighborhood with a high point density, the probability of picking random numbers that are less than or equal to the test value (δ) is (δ). Then, the probability of maintaining points in that neighborhood is (δ) and the probability of removing points in such neighborhood is (1 - δ) provided that we have enough samples in the neighborhood. An illustration of the adaptive down-sampling performance on a simulated circular point cloud with 4.0m radius is shown in Figure 2. The simulated point cloud has a maximum point density of 1200 pts/m^2 at the center and the point density reduces as we move towards the perimeter of the circular point cloud. In this example, the desired density is set to 400 pts/m^2. According to Equation 1, in the central area of the circle, the test value (δ) will be 1/3. Therefore, the portability of picking random values (r) that are less than or equal to 1/3 is 1/3. Therefore, this approach will maintain 1/3 of the points in the central neighborhood while removing the remaining 2/3 provided that we have enough samples within such neighborhood. In summary, using such approach, we can derive more uniformly-distributed points in areas with high point density while keeping points in neighborhoods with low point density intact.



(a) (b)

Figure 2. (a) The point density distribution before (a) and after (b) applying the adaptive down-sampling for a circular point cloud with 4.0m radius (Adapted from Al-Durgham, 2014)

2.2 Planar and Linear Feature Segmentation

To evaluate the impact of the adaptive, random, and point-spacing-based down-sampling strategies on subsequent data processing activities, we implement a region-growing segmentation procedure that simultaneously extracts planar and linear features from the original and down-sampled point clouds. The segmentation procedure is carried out through the following steps:

1. Randomly select a pre-specified percentage of the point cloud to act as seed points;
2. A local neighborhood for each seed point (seed region) is established;
3. For each of the seed regions, we perform a Principal Component Analysis (PCA) (Belton and Lichti, 2006) to judge whether the defined seed region belongs to planar, linear/cylindrical, or rough features;
4. For the classified planar and linear/cylindrical seed regions, we perform a least-squares adjustment procedure to determine the parameters of the best fitting plane or line/cylinder through each of the seed regions; and
5. Starting from the seed regions, we proceed with region growing using the estimated parameters for the enclosing feature.

2.3 Segmentation Quality Control and Evaluation

To evaluate the impact of the different down-sampling procedures on the segmentation, we implement quantitative quality control measures that have been introduced by Lari and Habib (2014). These measures will quantify the following:

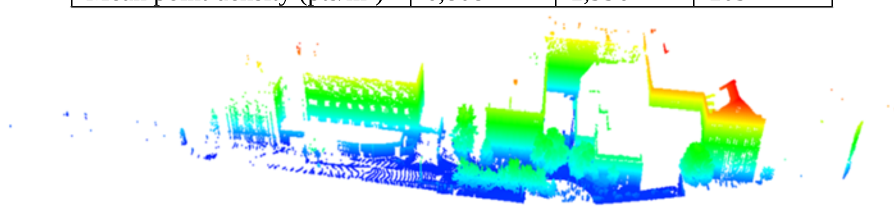
1. The frequency of non-segmented points, which should have been incorporated in any of the segmented features, and
2. The frequency of over-segmentation instances (i.e., instances where a single planar or linear/cylindrical surface have been segmented as two or more segments) in the segmentation results.
For both datasets, fewer instances (i.e., lower frequency) indicate a better segmentation. In addition to the above segmentation quality control measures, we also investigate the execution time of the segmentation and quality-control processes.

3. Datasets Description

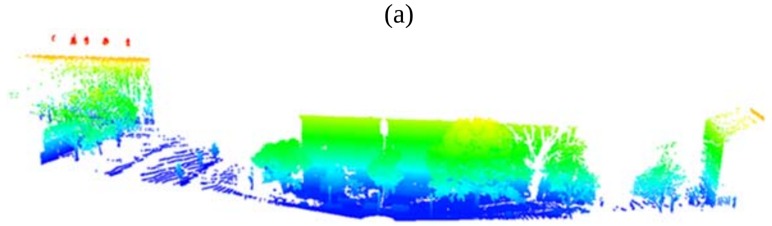
To comparatively evaluate the performance of the different down-sampling strategies, we use three sets of point clouds that are derived from TLS and imagery. Datasets 1 and 2 are collected from TLS (Leica HDS3000). The third dataset is generated from imagery captured by a UAV (Dji phantom 2) through dense matching. The specifications of the original datasets are shown in the Table 1. Table 2 shows perspective views of these datasets, where the assigned color is based on the height of the points.

Table 1. Specifications of the real datasets for the experimental results

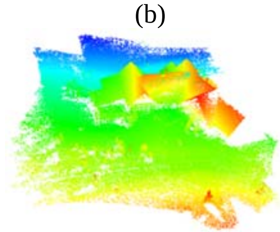
	Dataset 1	Dataset 2	Dataset 3
Number of points	2,765,436	785,243	230,434
Max. Point Density (pts/m^2)	562,239	24,071	1,264
Min. Point Density (pts/m^2)	0.002	0.002	0.092
Mean point density (pts/m^2)	6,808	1,996	109



(a)



(b)



(c)

Figure 3. Perspective views of datasets 1 (a), 2 (b), and 3 (c)

4. Experimental Results

In this section, we test the performance of three down-sampling strategies: 1) adaptive down-sampling; 2) random down-sampling; and 3) point-spacing-based down-sampling. The adaptive down-sampling is established using Equation 1 to have a pre-specified point-density value. Random down-sampling is applied using "Cloudcompare" to have a down-sampled dataset that has exactly the same number of points as the adaptively down-sampled dataset. For the point-spacing-based down-sampling, points are removed according to a set inter-point spacing, which corresponds to the pre-specified point density. The pre-specified desired point density and minimum distance for adaptive and point-spacing-based down-sampling for datasets 1, 2, and 3 are shown in Table 2 while the point density statistics for the original and down-sampled datasets are shown in Table 3.

From Table 3, one can see that the minimum point density values for the adaptively down-sampled and original datasets are exactly the same. This means that points in areas with sparse point density have been maintained. However, for the randomly and point-spacing-based down-sampled datasets, the minimum point density have decreased. The reason for that is the random down-sampling does not consider point density during the removal process. Therefore, in sparse areas that might have few neighboring points (i.e., some points whose distance is less than the pre-set distance), those points will be removed. For the point-spacing-based down-sampling, only the distances between neighboring points are considered. When two points are closer than a pre-set distance, points are removed. In the sparse area, the neighboring points could be removed according to the pre-set distance. We should also note that the adaptive down-sampling is the only approach that achieved the closest mean point density to the desired one. For the random and point-spacing-based down-sampling approaches, we can see that these methods had point density values that are significantly different from the desired one (i.e., either too small or too large).

Table 2. Down-sampling parameters for the adaptive and point-spacing-based approaches

	Adaptive down-sampling Desired point density (pts/m^2)	Point-spacing-based down-sampling Min. spacing between points (m)
Dataset 1	220	0.0674
Dataset 2	200	0.0707
Dataset 3	50	0.1414

Table 3. Statistics for the point-density values for the original and down-sampled datasets

	Original	Adaptive down-sampling	Random down-sampling	Point-spacing-based down-sampling
Dataset 1				
Number of Points	2,765,436	841,051	841,051	499,770
Max. Point Density (pts/m^2)	562,239.317	1,071.759	308,826.804	454.679
Min. Point Density (pts/m^2)	0.002	0.002	0.000	0.001
Mean point density (pts/m^2)	6,807.726	178.526	2,000.476	108.672
Dataset 2				
Number of Points	785,243	343,237	343,237	223,957
Max. Point Density (pts/m^2)	24,071.217	946.743	19,103.060	386.271
Min. Point Density (pts/m^2)	0.002	0.002	0.002	0.002
Mean point density (pts/m^2)	1,995.906	151.371	947.618	90.557
Dataset 3				
Number of Points	230,434	137,219	137,219	74,785
Max. Point Density (pts/m^2)	1,264.293	188.815	849.833	53.950
Min. Point Density (pts/m^2)	0.092	0.092	0.090	0.090
Mean point density (pts/m^2)	108.988	43.310	66.195	22.126

We then applied the region-growing-based segmentation on the original and down-sampled datasets. The segmentation execution time for the different datasets is shown in Table 4. In spite of the fact that the adaptive and random down-sampling approaches have the same number of points, the execution time for the adaptive down-sampled datasets is much better than that for random down-sampled point clouds. For the point-spacing-based down-sampled datasets, the number of points are much smaller than the adaptively and randomly down-sampled datasets.

Therefore, the segmentation execution time for that data set is less when compared to the adaptively and randomly down-sampled point clouds.

Table 4. Segmentation execution time for the different datasets

	Time **(hh:mm:ss)**			
Dataset	Original Dataset	Adaptive down-sampling dataset	Random down-sampling dataset	Point-spacing-based down-sampling dataset
1	01:10:46	00:11:30	00:17:51	00:05:17
2	00:33:17	00:05:43	00:06:00	00:02:51
3	00:03:31	00:01:33	00:01:41	00:00:50

The quality control procedure proposed by Lari and Habib (2014) is finally used to improve the quality of the segmentation results. The quality control measures are shown in Table 5. Due to space constraints, this paper will only investigate the qualitative aspects of the segmentation results. Quantitative measures will be thoroughly evaluated in future research publications. The segmentation results before and after the quality control are shown in Figures 4 to 15. Closer investigation of such results illustrate the comparative impact of the different down-sampling procedures. More specifically, problematic areas are marked for demonstrating the impact of the different down-sampling approaches on the segmentation quality. For dataset1, we can see that there is information loss when working with the randomly and point-spacing-based down-sampled datasets. Especially in randomly down-sampled dataset, some of segments are missed and some over segmentation problems could not be refined through the quality control process. For the point-spacing-based down-sampled datasets, identified problems could be caused by the sparse points in low-density areas and/or the region-growing process.

For the second dataset, we missed some segments in both the randomly and point-spacing-based down-sampled point clouds. For dataset 3, since the density values are similar for the different down-sampled point clouds, the differences between the segmentation outcomes are minor. However, we still missed small segments in the randomly down-sampled dataset and both the randomly and point-spacing-based down-sampled datasets have incomplete segments.

Table 5. Statistics of the quality control measures for the segmentation results from the different datasets

Dataset	Original Dataset	Adaptively down-sampled dataset	Randomly down-sampled dataset	Point-spacing-based down-sampled dataset
Dataset 1				
QC Non-Segmented Points	Time : 01:40:00	Time : 00:13:36	Time : 00:26:21	Time : 00:10:26
QC Over-Segmentation	Time : 06:57:59	Time : 01:23:45	Time : 01:12:47	Time : 00:39:10
Number of Planes after QC	276	130	126	79
Max. (pts/plane)	277,789	96,099	111,498	67,837
Min. (pts/plane)	20	29	42	29
Average (pts/plane)	6,045.329	4,153.829	3,916.738	3,831.089
Dataset 2				
QC Non-Segmented Points	Time : 00:23:57	Time : 00:04:40	Time : 00:06:12	Time : 00:01:57
QC Over-Segmentation	Time : 01:56:16	Time : 00:21:22	Time : 00:18:39	Time : 00:10:21
Number of Planes after QC	70	37	36	28
Max. (pts/plane)	251,316	118,585	109,334	78,653
Min. (pts/plane)	35	24	115	25
Average (pts/plane)	8,156.457	5,390.216	6,874.971	4,554.964

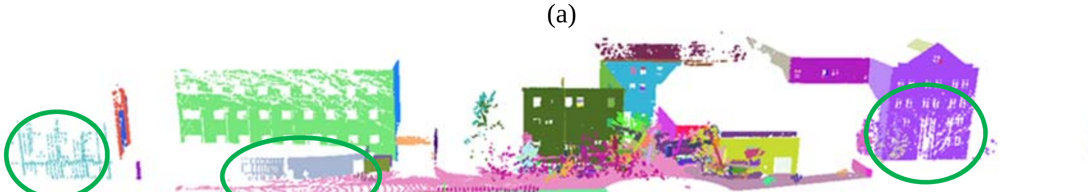
Dataset 3				
QC Non-Segmented Points	Time : 00:01:00	Time : 00:00:47	Time : 00:00:27	Time : 00:00:13
QC Over-Segmentation	Time : 00:21:39	Time : 00:07:31	Time : 00:09:38	Time : 00:10:21
Number of Planes after QC	33	18	22	22
Max. (pts/plane)	165,285	96,525	98,160	52,497
Min. (pts/plane)	20	65	47	34
Average (pts/plane)	6,511.273	5,107.583	5,759.045	3,009.227

(a)

(b)

Figure 4. Dataset1: Original Dataset – Planar segments (a) before and (b) after Quality Control

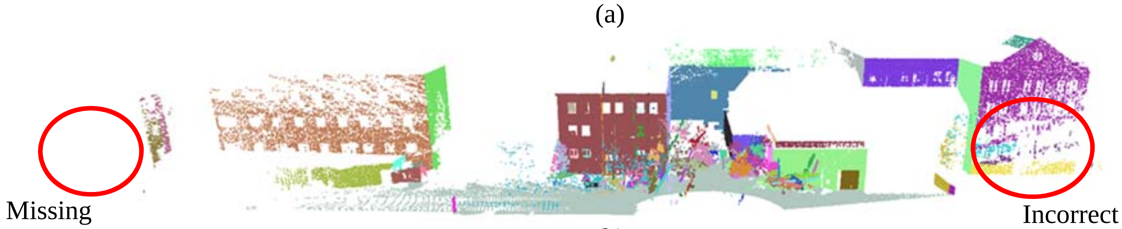
(a)



(b)

Figure 5. Dataset1: Adaptively down-sampled dataset – Planar segments (a) before and (b) after Quality Control

(a)



(b)

Figure 6. Dataset1: Randomly down-sampled dataset – Planar segments (a) before and (b) after Quality Control

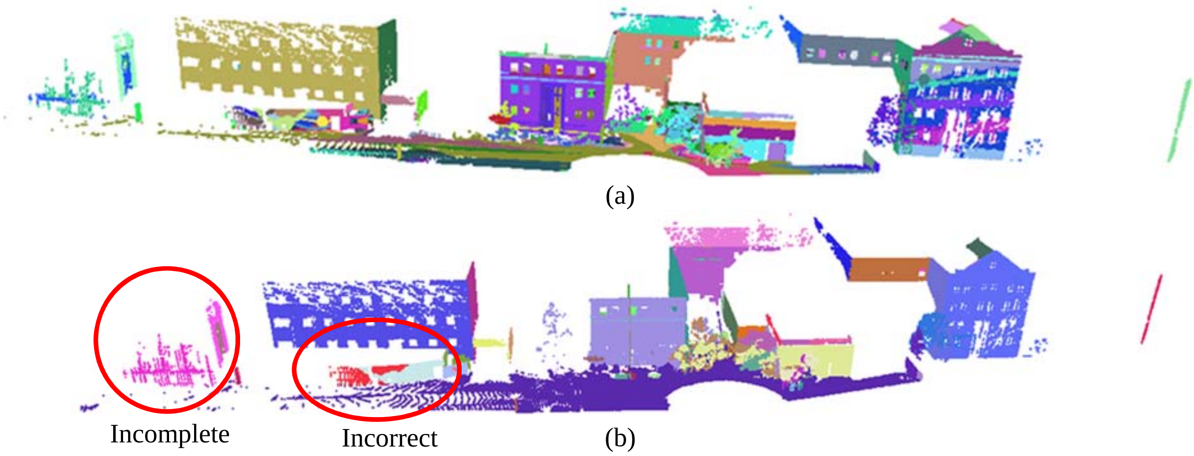


Figure 7. Dataset1: Point-spacing-based down-sampled dataset – Planar segments (a) before and (b) after Quality Control

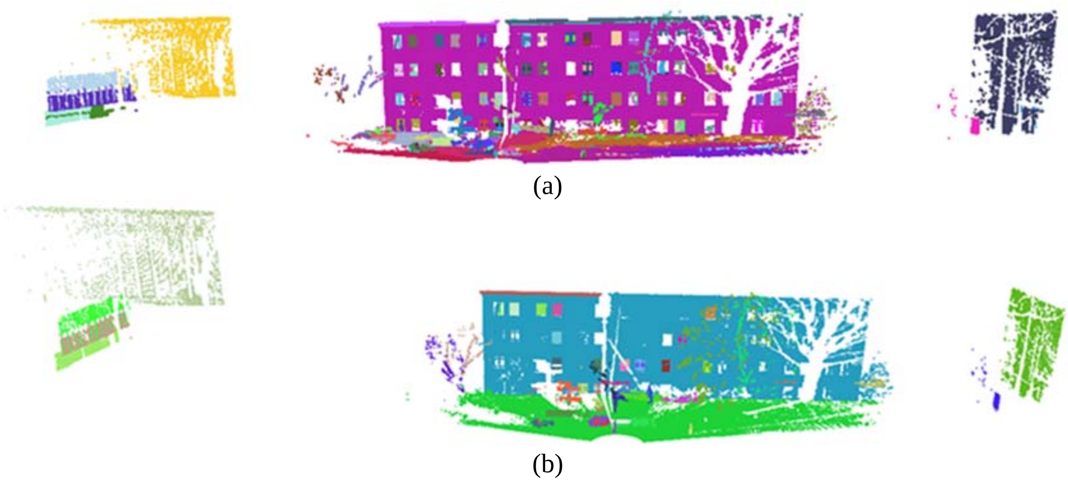


Figure 8. Dataset2: Original Dataset – Planar segments (a) before and (b) after Quality Control

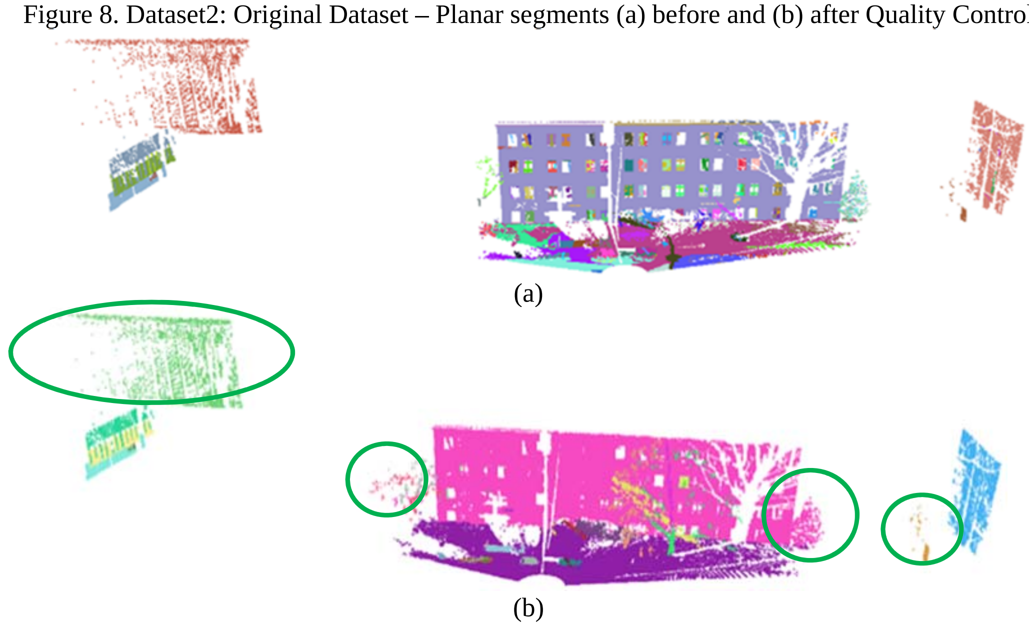


Figure 9. Dataset2: Adaptively down-sampled dataset – Planar segments (a) before and (b) after Quality Control

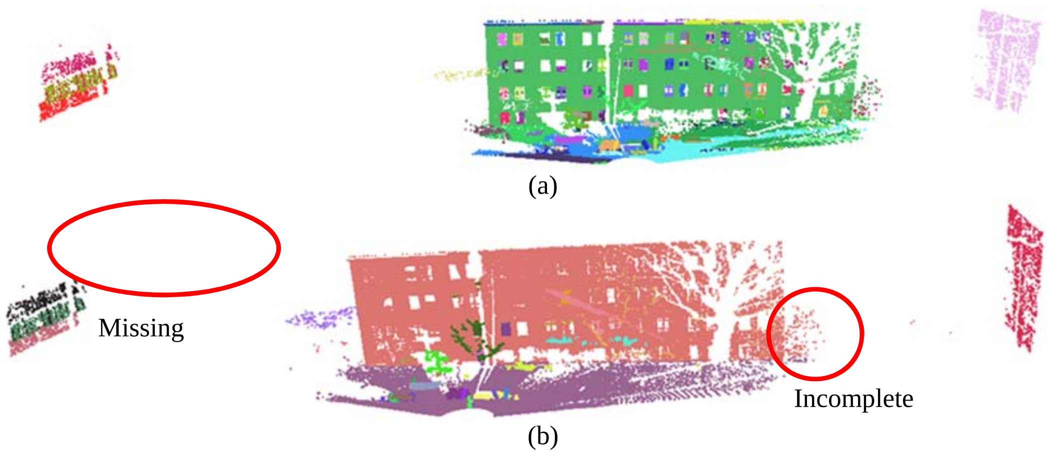


Figure 10. Dataset2: Randomly down-sampled dataset – Planar segments (a) before and (b) after Quality Control

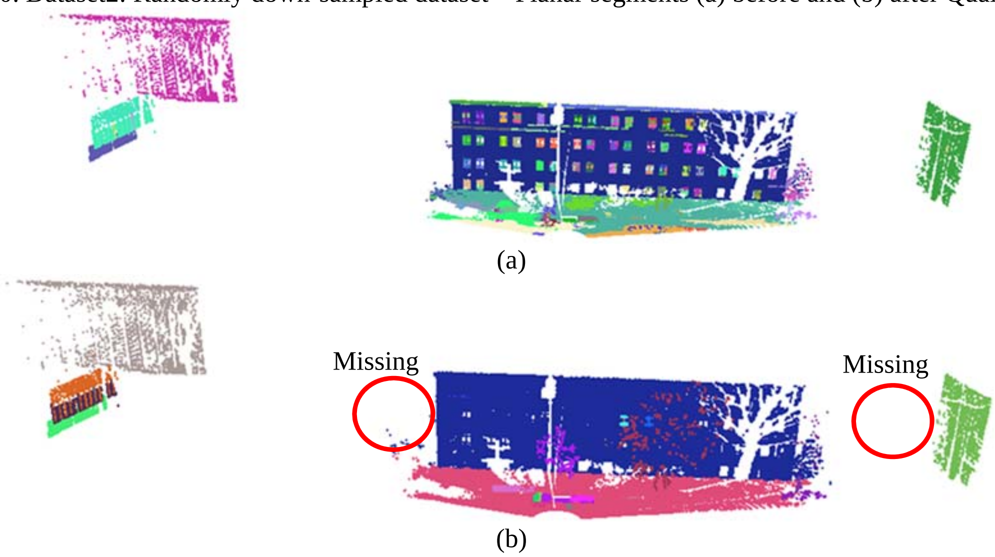


Figure 11. Dataset2: Point-spacing-based down-sampled dataset – Planar segments (a) before and (b) after Quality Control

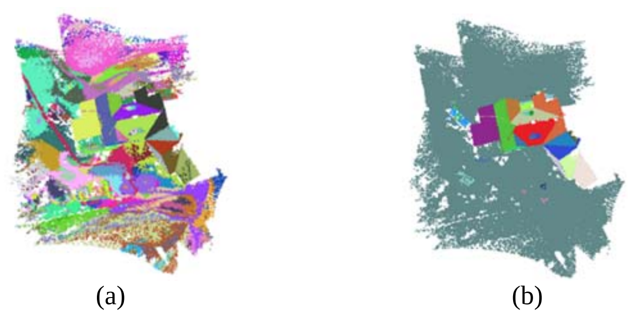


Figure 12. Dataset3: Original Dataset – Planar segments (a) before and (b) after Quality Control

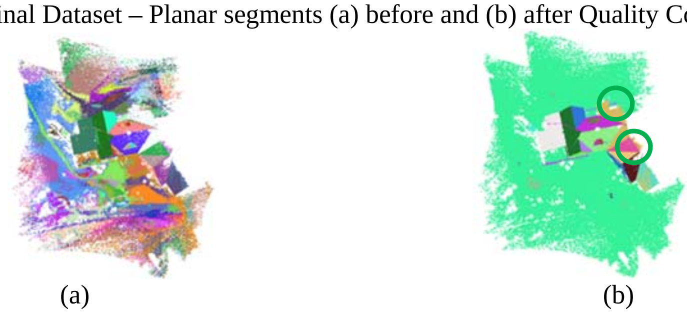


Figure 13. Dataset3: Adaptively Down-sampled dataset – Planar segments (a) before and (b) after Quality Control

(a) (b)

Figure 14. Dataset3: Randomly down-sampled dataset – Planar segments (a) before and (b) after Quality Control

(a) (b)

Figure 15. Dataset2: Point-spacing-based down-sampled dataset – Planar segments (a) before and (b) after Quality Control

5. Conclusions and Recommendations for Future Work

In this paper, we introduced an adaptive down-sampling strategy while comparing its performance through point density and segmentation results for three down-sampled datasets. More specifically, the segmentation of the original, adaptively down-sampled, randomly down-sampled, and point-spacing-based down-sampled point clouds are qualitatively and quantitatively evaluated. Through point density analysis, we demonstrated that compared with other methods, the adaptive down-sampling provides the closest mean point density to the desired one. Moreover, it keeps the points in sparse neighborhoods intact. The adaptive down-sampling also helped in speeding up the segmentation process when compared with a randomly down-sampled dataset that has the same number of points. We also evaluated the segmentation results after its quality control. It has been shown that some segments could be lost in the randomly and point-spacing-based down-sampled datasets. On the other hand, the adaptively down-sampling dataset maintained the major details in the different datasets.

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