Automatic Building Extraction from Terrestrial Laser Scanning Data

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***Abstract*—The extraction of building from the huge amount of point clouds with different local densities, especially in the presence of random noisy points, is still a formidable challenge. In this paper, we present a complete strategy for building extraction from terrestrial laser scanning data. First, a novel segmentation method is proposed to facilitate the task of building extraction. The points are grouped based on the normals and the adjacency relationships. Second, the planar surfaces are recognized from the segmentation results based on the properties of the Gaussian image. Finally, the buildings are extracted from the urban point clouds based on a collection of characteristics of point cloud segments like shape, normal direction and topological relationship. Experimental results demonstrate that the proposed method can be used as a robust way to extract buildings from terrestrial laser scanning data. At the same time, the buildings are decomposed into several patches which lay a good foundation for building reconstruction.**

***Index Terms*—building extraction, point cloud segmentation, plane recognition, terrestrial laser scanning.**

I. Introduction

Numerous practical applications are related to buildings, such as virtual tourism, urban planning and environmental monitoring. Therefore, automatic extraction of building from laser scanner data becomes necessity due to the growing demand for urban planning and virtual tourism, coupled with the advance in 3D data acquisition technology. In the last decade, extensive studies about building extraction have been undertaken on LiDAR(Light Detection and Ranging) data[1-4] or image data[5]. However, since urban scenes need to be realistic not only from a bird's point of view, but also from a pedestrian's point of view, the extraction of building from TLS(Terrestrial Laser Scanning) data becomes essential. Recent advances in sensing and laser technologies make TLS become a common way to acquire 3D data of complex urban scenes. Unfortunately, although techniques for the acquisition of 3D urban point clouds via TLS have constantly been improved, processing these large 3D data sets in order to extract static entities such as buildings and roads is still a formidable challenge. This is due essentially to the difficulties of exploring directly and automatically valuable spatial information from the massive unstructured 3D data.

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In this paper, a complete strategy for building extraction from TLS data is proposed. The inspiration of our method comes from the facts that a majority of buildings in existence nowadays could be represented by planes. At the same time, ground and grass can also be represented by using one or a group of large planar surfaces. Due to the facts mentioned above, we present a clustering algorithm for extracting homogeneous segments in point clouds based on the normals and the adjacency relationships of the points. Then the planar surfaces are recognized based on the Gaussian image. After recognizing the ground in advance, the planar surfaces belonging to the buildings are extracted. The whole process of our method is described as follows with the flowchart in Fig. 1.

(1) Segmentation. A novel clustering method for reliable and efficient segmentation of the urban point clouds is proposed. The clustering method requires no prior clustering number compared to the K-means clustering method.

(2) Plane recognition. Since most of the building components in existence nowadays are planes, a novel method is introduced to recognize the planar surfaces based on the properties of the Gaussian image.

(3) Building extraction. This process tries to identify the surfaces belonging to the buildings from the given 3D point clouds. We first recognize the ground based on the position and normal direction of the planar surfaces. Besides the planes completely containing in the Oriented Bounding Box(OBB) of the ground, the residual planes are considered as the buildings.

The remainder of the paper is organized as follows. After a brief review of point cloud segmentation techniques in Section 2, Section 3 presents our segmentation method in detail. The method of building extraction is proposed in section 4 and experimental results are shown in section 5. The limitations of our method and future research are indicated in the last section.

II. Related Work

Object extraction from TLS data has been a research domain in recent years. Segmentation, the process which partitions point clouds into regions with homogeneous property, is an essential step which needs to be performed prior to object extraction. Many methods are known in literature for point clouds segmentation, which roughly fall into the following categories:

Model-based: this strategy tries to fit primitive shapes like planes, cylinders or spheres in the point cloud.

RANdom SAmple Consensus (RANSAC)[6] and Hough transform[7] are two widely known model fitting methods. Tarsha-kurdi[8] applied RANSAC and Hough transform for automatic detection of 3D building roof planes from LiDAR data. After a comparison of both algorithms in terms of processing time and sensitivity to point cloud characteristics, this analytic study shows that RANSAC algorithm is still more efficient than the Hough transform. On the other hand, the Hough transform is very sensitive to the segmentation parameter values. RANSAC extracts shapes by randomly drawing minimal set from the point data and constructing corresponding shape primitives. Its principle is well explained by[6,12]. Chaperon[9] used RANSAC and the Gaussian image to find cylinders in 3D point clouds. This method does not consider a larger number of different classes of shape primitives. Roth[10] described an algorithm that uses RANSAC to detect a set of different types of simple shapes in the image domain or on range images which cannot process large unstructured 3D points. Nister[11] proposed an acceleration technique for the case that the number of candidates is fixed in advance. Schnabel[12] introduced another efficient RANSAC variant for primitive shape detection in point clouds. Tarsha[13] extended RANSAC algorithm to detect building roof planes from LiDAR data. Although many objects in the urban scene can be decomposed into geometric primitive shapes, there are a manifold of object types, which is subject to a diversity of topology, density and point distribution. No single geometric primitive is likely to describe all the objects sufficiently well. As a result, the robustness against noise and irregular shapes hinder the RANSAC as a suitable choice from segmenting the urban point clouds.

Data-driven: this strategy is motivated by the recognition that points belonging to a segment tend to obey a proximity constraint and cluster if represented by adequate features[14]. The region growing methods and clustering-based methods are always used. The region-growing methods[15-18] always start with a seed point and then growing based on one or more criteria for accepting points into plane. This method may suffer from the over or under-segmentation and the problem of initial seed choice. Moreover, different choices of seed may result in different segmentation outputs. Compared to region-growing methods, the clustering-based methods are more efficient because of the generality and flexibility it offers in accommodating spatial relations between points and attributes for data segmentation[19]. Clustering-based method is a variety of procedures aiming at grouping the data into homogeneous patterns. Parametric clustering algorithms, such as K-means clustering, are used in some segmentation methods[20]. However, severe obstacle to K-means clustering algorithm is the fact that it needs to know the number of clusters beforehand and improper assumptions may lead to unsatisfactory segmentation results. Mean-shift[21,22], a nonparametric clustering method, has none of the above limitation. Liu[23] proposed a nonparametric clustering algorithm to segment CAD models. Based on the mean-shift, cell mean shift(CMS) is developed to cluster points on Gaussian sphere. The proposed method is only tailed to the CAD models with regular shapes. Biosca[24] presented an unsupervised robust clustering approach based on fuzzy methods to extract homogeneous segments from unorganized point cloud. Both the Fuzzy C-Means(FCM) algorithm and the Possibilistic C-Means(PCM) mode-seeking algorithm are used in combination with a similarity-driven cluster merging method. Klasing[25] presented a radially bounded nearest neighbor(RBNN) clustering strategy to segment 3D point cloud. The method failed to produce meaningful segments when objects can be connected by a continuous string of points through some common supportive surfaces.

In this paper, we present a novel method to automatically segment large raw point clouds. Contrary to the K-means clustering algorithm, our method does not rely on the prior assumptions. In addition, the proposed method is robust to the urban point clouds with noise and deficiency. Our method can not only extract the buildings from the urban point clouds, but also decompose the buildings into several patches which lay a good foundation for building reconstruction.

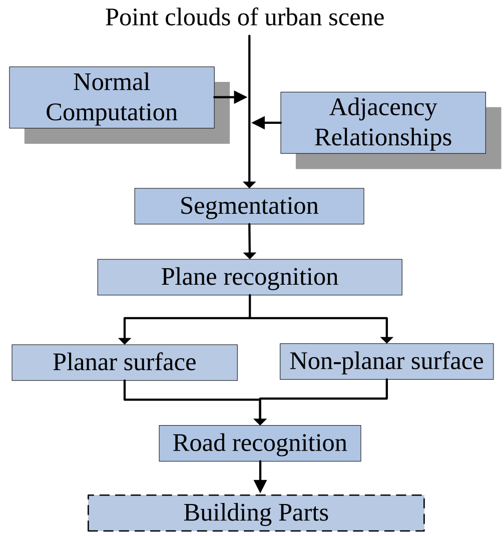


Figure 1. Overview of our method

III. POINT CLOUD SEGMENTATION

Segmentation is an essential step in the processing of point cloud, and the quality of building extraction from laser data is highly dependent on the validity of the segmentation results. K-means clustering algorithm often relies upon the correctly specifying parameters and has embedded assumptions. Different assumptions may lead to different segmentation results. The new clustering algorithm proposed in this paper has none of the above limitations.

The idea of point segmentation is grouping the 3D points based on the normals and the adjacency relationships.

We set two criteria to check whether a pair of points, p and q, lie on the same segment:

1. n_p and n_q are roughly parallel, i.e., $n_p \cdot n_q$ is close to 1.

2. The distance between point p and q is less than a threshold r.

Again, we should set two thresholds, ε and r, to screen the parallelism of the normals of p and q, and the distance between the two points.

Thus the normal of the point is a key attribute which is calculated by[26]. First, we cluster the original point clouds based on the point normals. The points with the parallel normals should be grouped to a cluster. After grouping the points, we find there is a certain distance between the parallel surfaces in the point clouds. We propose a distance-based clustering algorithm to segment the parallel surfaces. The points p_i and p_j are classified into the same cluster if the distance between p_i and p_j is less than the threshold r . Algorithm 1 shows a detailed description of segmentation method.

Algorithm 1

Input: The original point clouds: $p_1, p_2 \dots p_m$

Output: The segmentation results: cluster $T_1, T_2 \dots T_m$

for i=0 to size({Point Clouds})

if the current point p *has been marked, do*

Go to the next point.

else

for the current point p_i *, set* $n_s \leftarrow n_{p_i}$

Step through the list of all points

if (point p_j *is not clustered and* $n_s \cdot n_{p_i} \le \varepsilon$ *),do*

p_i *and* p_j *are assigned to a cluster* C_i

end if

end if

end for

for each clusters C_i *with the roughly parallel normals, do*

for m=0 to size ({Clusters C_i *}) do*

find all the neighbors NN of p_m *within distance r using k-d tree*

if all the points $u_j \in NN$ *have not assigned then*

assign all the neighbors to a new cluster

else

find the minimum label of the assigned point: mLabel

assign all the neighbors to cluster T_{mLabel}

end if

end for

end for

for the final cluster T_i *, do*

if $T_i.size() < 10$ *then*

delete(T_i *)*

end if

end for

Fig. 2 shows the segmentation results by using Algorithm 1.

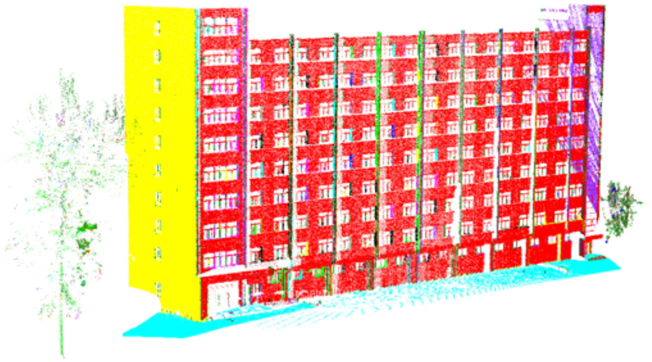
IV. Knowledge Based Building Extraction

Each object in the urban scene has its own characteristics. Since the characteristics can be formulated as feature constraints that are understandable by machines, automatic extraction of building from TLS data becomes possible.

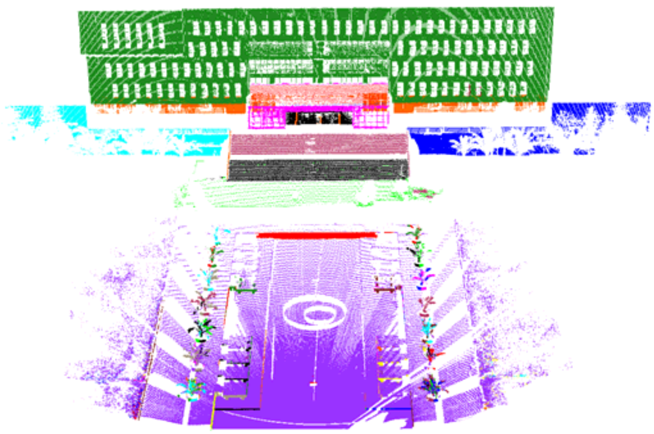
4.1 Feature Constraint

The extraction algorithm is proposed based on the following assumption:

Basic assumption: surfaces of a building exhibit planarity and it can be represented by several planar surfaces.



(a) Data1



(b) Data2

Figure 2. Segmentation results of different point clouds

A majority of buildings in existence nowadays satisfy this assumption[17]. Considering the human knowledge about buildings, ground and trees in the urban scene, we summarized a set of feature constraints as below:

1. **Shape constraint**: Man-made objects often have regular and common shapes. Building walls, ground and grass can be represented by using one or a group of large planar surfaces with different surface normals. However, due to the diversity of tree types, there is no regular shape to represent the trees. Buildings and ground can be easily distinguished from the trees or noise segments by their shape information.
2. **Direction constraint**: The normal of ground is always vertical.
3. **Position constraint**: Certain features appear only in certain position. For example, the ground is always the segment with the lowest position compared to other planes.
4. **Topology constraint**: Planes belonging to the buildings have certain topology relation with other planes. For example, the planes which are contained completely in the OBB(Orientation Bounding Box) of the ground are not the parts of the building.

We list the 4 feature constraints for the main objects in the urban scene in Table I.

4.2 Plane Recognition

After segmentation, we should first recognize the planar surfaces in the urban point clouds. Gaussian images are useful for representing the shape of surfaces[27]. We use the following property to recognize the planar surface.

TABLE I. FEATURE CONSTRAINTS OF DIFFERENT OBJECTS

Object	Shape	Position	Normal Direction	Topology
Building	Planar surface	Above the road	----	----
Ground	Planar surface	Lowest	Vertical	----
Other planar patches	Planar surface	Above the road	----	Contain in the OBB of ground
Trees	Non-planar	Above the road	Irregular	----
Noise	Non-planar	Above the road	Irregular	----

Property 1: If all the points of a surface are planar points, the Gaussian image of the surface is a point. On the contrary, if the Gaussian image of a surface is a point, the surface is a planar surface.

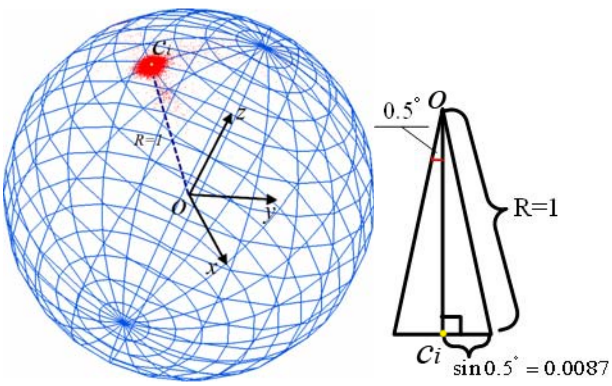
Suppose $T_1, T_2 \ldots T_m$ are the segmentation results and $G(T_1), G(T_2) \ldots G(T_m)$ are the Gaussian image of $T_1, T_2 \ldots T_m$. Due to the noise and inaccuracy in normal estimation, normal distribution of the planar surface may not exactly be a point on the Gaussian sphere. They just look like gathering to a small and nearly flat area. As shown in Fig. 3(a), there is the Gaussian image of a planar surface. The area marked in the red color is the normal distribution of a planar surface. In order to recognize the planar surface, we should judge whether the normals of the cluster locate on a small area on the Gaussian sphere.

Assume $G(T_i)$ is the Gaussian image of segment T_i, the center c_i (yellow point in Fig. 3(a)) of $G(T_i)$ is calculated by Equation (1):

$$c_i = \frac{1}{N}\sum_{i \in N} G(p_i) \qquad (1)$$

Where $p_i \in T_i$ and N is the total number of segment T_i.

Then, connect point c_i and the center of Gaussian sphere O. Gaussian sphere is a unit ball whose radius R is 1. As shown in Fig. 3(b), according to the triangular calculation: $\sin 0.5^{\circ} = 0.0087, d = 0.0087 * 2 = 0.0174$ .Count the number of points whose distance to c_i is less than 0.0174. If the number account for 70% of the cluster number, the surface is defined as a planar surface.



(a)Gaussian image of planar surface (b) Triangular calculation

Figure 3. Gaussian image of a planar surface

4.3 BUILDING EXTRACTION

After recognizing the planar surfaces in the urban point clouds, we extract the buildings based on the feature constraints listed in Table I.

The implementation of building feature recognition is given below as an example. For a planar surface P_i, we compute the central points $(\bar{x}, \bar{y}, \bar{z})$ of P_i and the average normal $(\bar{n}_x, \bar{n}_y, \bar{n}_z)$ by using Equation (2) and (3):

$$\bar{x} = \frac{1}{N}\sum_{i \in N} x_i, \bar{y} = \frac{1}{N}\sum_{i \in N} y_i, \bar{z} = \frac{1}{N}\sum_{i \in N} z_i \qquad (2)$$

$$\bar{n}_x = \frac{1}{N}\sum_{i \in N} n_{xi}, \bar{n}_y = \frac{1}{N}\sum_{i \in N} n_{yi}, \bar{n}_z = \frac{1}{N}\sum_{i \in N} n_{zi} \qquad (3)$$

Where (x_i, y_i, z_i) is one point in surface P_i and $(\bar{n}_{xi}, \bar{n}_{yi}, \bar{n}_{zi})$ is the normal of point (x_i, y_i, z_i). N is the total number of surface P_i.

As we know, the normal of the ground is vertical which has the following features: two of them are close to 0 and the absolute value of the rest one is close to 1. However, the directions of three coordinates x, y, z are uncertain by using the terrestrial laser scanner. Not all the *z*-coordinate of the ground normal equals 1.

First, compute the average normal of each planar surface using Equation (3). Then, find the planar surfaces having the following features: two values of plane normals are close to 0 and the absolute value of the rest one is close to 1. At the same time, the coordinate Q equaling 1 should be marked. Next, the surface having the maximum absolute value of Q-coordinate is recognized as the ground. Due to the diversity of the road in the real world, the planar surfaces whose distance to the ground is less than a threshold σ are also recognized as the ground. Finally, we compute the OBB of the ground. Besides the planar surfaces completely contained in the OBB of the ground, the residual planar surfaces are recognized as the building parts.

Algorithm 2 shows a detailed description of building extraction algorithm.

Algorithm 2

Input: Planar clusters planeList: $P_1, P_2 \ldots P_m$

for(i=0; i<planeList.size(); i++)

Compute the average normal of cluster P_i *: planeList [i].Normal:* $(\bar{n}_x, \bar{n}_y, \bar{n}_z)$ *,and the central point: planeList [i].Center:* $(\bar{x}, \bar{y}, \bar{z})$

if($\bar{n}_x \approx 0, \bar{n}_y \approx 0, fabs(\bar{n}_z) \approx 1 \,||\, fabs(\bar{n}_x) \approx 1, \bar{n}_y \approx 0, \bar{n}_z \approx 0 \,||\, \bar{n}_x \approx 0, fabs(\bar{n}_y \approx 1), \bar{n}_z \approx 0$ *) then*

the plane is the ground or the building wall paralleling with the ground

if($fabs(\bar{n}_j) \approx 1)$ $j \in \{x, y, z\}$ *then*

if(fabs(planeList [i].Center.j) is maximum) then

the Planar Cluster planeList[g] is the ground

End if

End if

if(fabs(planeList[j].Center.j -planeList[g] .Center.j)< σ *)*

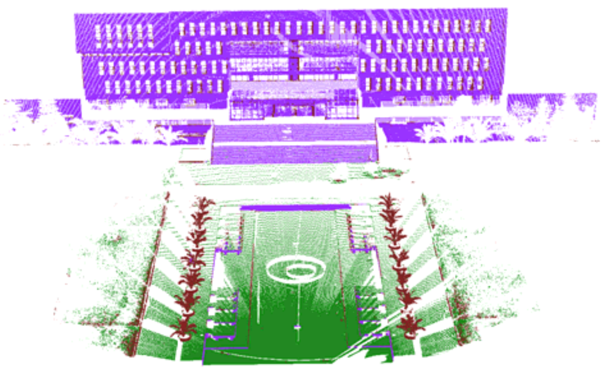
the Planar Cluster planeList[j] is also the ground
End if
end if
End for
Computer the OBB for the ground
Recognize the planar surfaces in the OBB. The residual planar surfaces belong to the buildings.

TABLE II. AVERAGE NORMALS OF GROUND OF DIFFERENT DATA

Data set	Average normals of ground	Coordinate close to 1 or -1
Data1	(0.0236,-0.9897,0.0287)	*y*-coordinate
Data2	(0.0025,0.0066,0.9936)	*z*-coordinate
	(-0.0326,-0.0265,0.9942)	

Table II shows the average normals of the ground of Data1 and Data2. In Data1, coordinates x and z are close to 0, and the absolute value of coordinate y is close to 1. However, in Data2, coordinates x and y are close to 0, and coordinate z is close to 1.

(a) Data1



(b) Data2

Figure 4. Classification of the different point clouds

As shown in Fig. 4, the points with purple and green are planar points and the brown are non-planar points(noise and trees). The green points belong to the ground surfaces which are recognized by our method. As shown in Fig. 4(b), there are many small planes around the ground surfaces. We should compute the OBB of the ground. If a plane is contained in the OBB completely, it should be removed and the residual planes belong to the buildings.

V. Experiments

5.1 Results

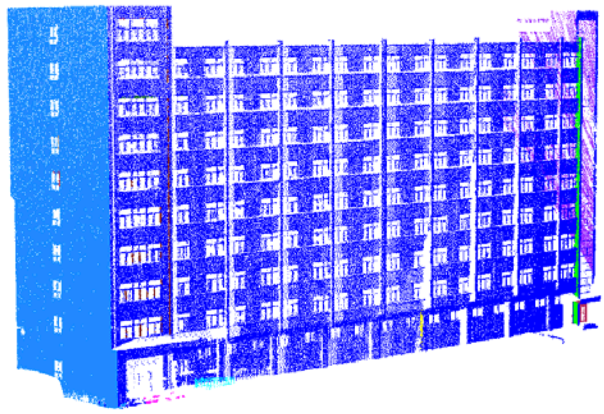
The experimental datasets were acquired by Topcon scanner GLS-1500. The proposed algorithms are programmed with VC++ and OpenGL for display and rendering. All the experiments in this paper are carried out on a PC with Intel(R) Core(TM) 2，CPU 2.80GHz，2G memory.

The parameters ε and r used in section 3 depend on the concrete urban scene. In this paper, the threshold ε is set as 0.1. The threshold r is usually set between 0.05 and 0.1. In addition, the threshold σ used in section 4.3 is set as 0.5 in this paper. Table III shows the point number of different parts in urban point clouds. It can be seen that our method are also effective in the urban point clouds with high noise. Fig. 4 demonstrates that the plane recognition method proposed in this paper is robustness and efficiency.

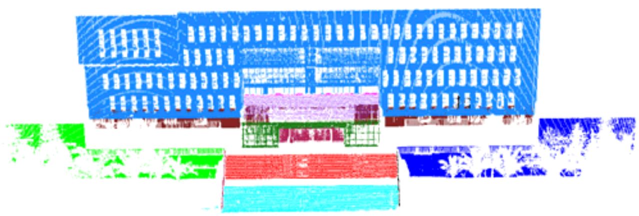
TABLE III. POINTS NUMBER OF DIFFERENT PARTS

Data set	Total number	Plane points	Building points	Trees and noise	Noise ratio
Data1	658622	600736	545314	57886	8.8%
Data2	799501	690730	162133	108771	13.6%

Fig. 5 displays the building parts of different urban point clouds. All these results were created in sequence and automatically. The buildings are segmented to different planes which lay a good foundation for building reconstruction. Although data obtained from outdoor long range scanning suffer from noise, self and inter-object occlusion (Fig. 5), our method can also obtain promising results. It can be seen that all the parallel planar surfaces have been extracted successfully and no spurious surfaces occur in the stairs of Data2.



(a) Building parts of Data1

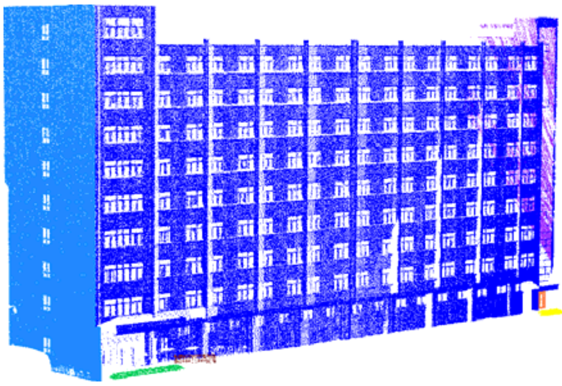


(b) Building parts of Data2

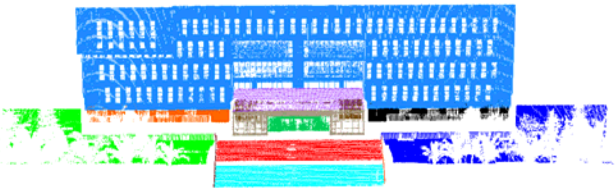
Figure 5. Building parts of different point clouds

5.2 Comparison

As shown in Fig. 6, the building parts of different point clouds are extracted by hand. At the same time, the buildings are segmented manually. Different surfaces are labeled with a unique color for illustration. It can be found that the proposed method in this paper has good performance for TLS data. The building parts extracted by using our method are almost correct. Compared to the manually segmentation result of Data1 (Fig. 6(a)), the beams and windows of the building are also segmented separately (Fig. 2(a)).



(a) Building parts of Data1



(b) Building parts of Data2

Figure 6. Manually labeled results of different point clouds

VI. Conclusion

This paper presents a method for building extraction from TLS data. The extraction involves segmentation and plane recognition. A novel clustering approach is proposed to automatically segment large urban point clouds without prior knowledge. The segmentation can be considered as a process of decomposing the TLS data into primitive shapes. Then, the planar surfaces are recognized based on the properties of the Gaussian image. Finally, buildings are extracted from the urban point clouds based on a collection of characteristics of the segments. The comparison between the results by using our method and the manually labeled results shows the effectiveness and robustness of our algorithm.

Considering our method is limited to the building composed of planar surfaces, a more robust shape recognition method should be discussed to detect more basic shapes in the future. Such an extension could improve the capacity of the proposed method and enable complete building extraction from more complex urban scenes.

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