3D Point Cloud Segmentation: A survey

Anh Nguyen[1] Bac Le[2]

***Abstract*— 3D point cloud segmentation is the process of classifying point clouds into multiple homogeneous regions, the points in the same region will have the same properties. The segmentation is challenging because of high redundancy, uneven sampling density, and lack explicit structure of point cloud data. This problem has many applications in robotics such as intelligent vehicles, autonomous mapping and navigation. Many authors have introduced different approaches and algorithms. In this survey, we examine methods that have been proposed to segment 3D point clouds. The advantages, disadvantages, and design mechanisms of these methods are analyzed and discussed. Finally, we outline the promising future research directions.**

I. INTRODUCTION

Fully three dimensional scanners are now widely available. In particular, with scanners such as Light Detection and Ranging (LIDAR) and Microsoft Kinect, 3D point clouds can be easily acquired for different purposes. The explosion of point cloud data need a library to process them. Point Cloud Library (PCL) [11] was introduced in 2011. This library contains state of the art algorithms for 3D perception. With the development of hardware and PCL, processing point clouds gains more and more attraction in robotics, as well as other fields.

The segmentation of point clouds into foreground and background is a fundamental step in processing 3D point clouds. Given the set of point clouds, the objective of the segmentation process is to cluster points with similar characteristics into homogeneous regions. These isolated regions should be meaningful. The segmentation process could be helpful for analyzing the scene in various aspects such as locating and recognizing objects, classification, and feature extraction.

In computer graphics, intensive researches have been done to decompose 3D model into functionally meaningful regions. The general way is build a graph from the input mesh, and cluster the graph to produce a segmentation by using information such as normal direction, smoothness, or concavity along boundaries. Shamir [7] survey variety of methods have been proposed for this problem: convex decomposition, watershed analysis, hierarchical clustering, region growing, and spectral clustering. Many of these approaches have been used widely to segment point cloud data, especially in region based methods [26] [32] [21] [19] [43].

[1]Anh Nguyen is Graduate Research Fellow at Computer Science Department, Information Technology Faculty, University of Science, Vietnam `nqanh@fit.hcmus.edu.vn`

[2]Dr. Bac Le is Associate Professor and dean of Computer Science Department, Information Technology Faculty, University of Science, Vietnam `lhbac@fit.hcmus.edu.vn`

In computer vision, segmenting 2D images is a classic problem and has been studied for several decades. It attracts a significant amount of work [10] [40] [27]. One of the most popular approach is graph clustering (e.g. Graph Cuts [4] including Normalised Cuts [36] and Min Cuts [14]). The idea of these methods have been used widely to segmenting 3D point cloud data [9] [12] [44]. However, Anand [2] showed that when a 2D image is formed from the corresponding 3D world, we will lost a lot of valuable information about the 3D shape and geometric layout of objects.

The work of Anguelov [9] suggested a 3D point cloud segmentation algorithm should have three important properties. First, the algorithm should be able to take advantage of several qualitatively different kinds of features, such as trees will have distinguished features from cars. When the number of features grows, segmentation algorithm should be able to learn how to trade them off automatically. Second, segmentation algorithm should be able to infer the label of points which lie in sparsely sampled regions based on the information of their neighbors. Third, the segmentation algorithm should adapt to the particular 3D scanner used, because different laser scanners produce qualitatively different point cloud data, and they may have different properties even with the same scene.

In the next section, we outline the main challenges of the field as these motivate the various approaches. Then, we briefly describe the common available 3D point cloud datasets. We classify and discuss in detail segmentation methods in section 3. While many works have been proposed, we do not intend to give complete coverage of all works in the area. In section 4, we discuss limitations of the state of the art and outline future directions.

II. CHALLENGES AND DATASETS

A. Challenges

We can precisely determine the shape, size and other properties of the objects in 3D data. However, segmenting objects in 3D point clouds is not a trivial task. The point cloud data are usually noisy, sparse, and unorganized. The sampling density of points is also typically uneven due to varying linear and angular rates of the scanner. In addition, the surface shape can be arbitrary with sharp features and there is no statistical distribution pattern in the data [31]. Moreover, due to the limitations of the 3D sensors, the foreground is often highly entangled with the background. These problems present a difficult challenge when designing a segmentation algorithm.

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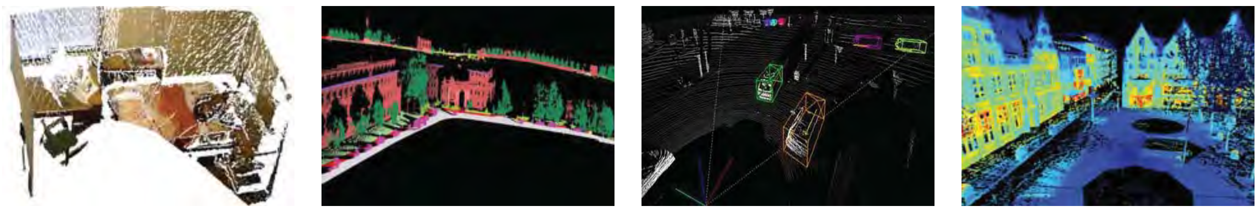

(a) (b) (c) (d)

Fig. 1. Example scenes of (a) Cornell RGBD dataset, (b) VMR-Oakland dataset, (c) KITTI dataset, and (d) Robotic 3D Scan Repository

B. Datasets

Recently, more point cloud datasets have been introduced (Fig. 1). These datasets can be classified into two categories: Indoor datasets which are captured by Kinect, and outdoor datasets which are usually captured by laser scanners such as LIDAR. The use of public datasets allows us to compare different approaches and gives insight into the advantages and disadvantages of these methods.

Cornell RGBD dataset [2]: This dataset has 52 labeled indoor scenes of point clouds with RGB values (24 labeled office scenes and 28 labeled home scenes). Point cloud data are created from original RGB-D images using RGBDSLAM [45]. The dataset composed from about 550 views, having 2495 segments labeled with 27 object classes.

VMR-Oakland dataset [35]: This dataset contains labeled point cloud data collected from a moving platform around CMU campus. The points was collected using laser scanner and are saved in text format, three real valued coordinates of each point are written in each line. The training, validation and testing data are also available.

KITTI dataset [29]: This dataset includes a large number of unorganized point clouds that were captured by a 360° Velodyne laser scanner. It was manually annotated ground truth bounding boxes for outdoor objects such as cars, pedestrians, trams, trucks, and cyclists.

Robotic 3D Scan Repository [20]: This repository provides collection of 3D point cloud datasets for both indoor and outdoor environments. Some datasets include thermal and color information. This is the huge collection of 3D point cloud data and can be use not only for segmentation but also for different purposes. However, these datasets have not been labeled, and they also may need a preprocessing step before using them as input for segmenting algorithms.

III. METHODS

In this section, we discuss the methodologies have been suggested for the segmentation of 3D point clouds. We generally categorized them into five classes: edge based methods, region based methods, attributes based methods, model based methods, and graph based methods (Fig. 2).

A. Edge based methods

Edges describe the characteristics about the shape of objects. Edge based methods detect the boundaries of several regions in the point clouds to obtain segmented regions. The principle of these methods is locate the points which have rapid change in the intensity. Bhanu et al. [13] proposed an edge detection technique by computing the gradient, fitting 3D lines to a set points and detecting changes in the direction of unit normal vectors on the surface. Jiang [37] presented a fast segmentation method using scan line grouping technique. Scan lines of the range image are splitted into curves, and they are then clustered to represent surfaces. Compared to Bhanu et al. [13], this method is advantageous in both segmentation quality and running time. But it is only suitable for range image, and not good for uneven density point clouds. In [22], authors proposed a new edge detection strategy by extracting close contours from a binary edge map for fast segmentation.

Although edge based methods allow fast segmentation but they have accuracy problems because all of them are very sensitive with noise and uneven density of point clouds, situations that commonly occur in point cloud data.

B. Region based methods

Region based methods use neighborhood information to combine nearby points that have similar properties to obtain isolated regions and consequently find dissimilarity between the different regions. Region based methods are more accurate to noise than edge based methods. But they have problem with over or under segmentation and determining region borders accurately. We divide region based methods into two categories: seeded-region (or bottom-up) methods and unseeded-region (or top-down) methods.

Seeded-region methods start the segmentation process by choosing a number of seed points, then from these points, each region will grow by adding neighbour points if they satisfy certain criterion or compatibility thresholds. The initial algorithm was introduced by Besl [26]. This algorithm includes two steps: identification of the seed points based on the curvature of each point and growing them based on predefined criteria such as proximity of points and planarity of surfaces. A drawback of this method is it is very sensitive with noise, and is time consuming. Several subsequent works proposed improvements to this initial method. Köster [21] presented an algorithm generates an irregular graph pyramid to store relative information between regions. This information is used to compare and merge adjacent regions. The work of Rusu et al. [19] used seeded-region methods based on smoothness constraint as described in [39]. In [32], Tovari introduced a region growing method for airborne laser data. This approach proposed a method for growing the seed

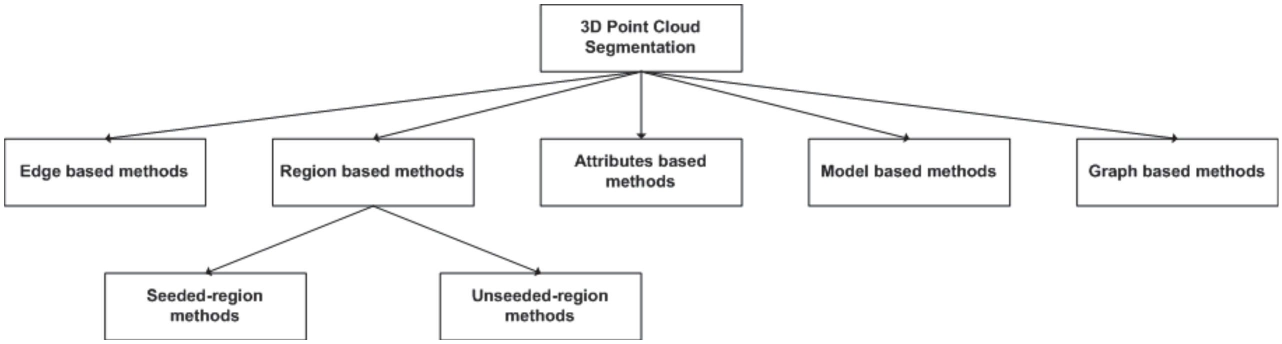

Fig. 2. Taxonomy of 3D point cloud segmentation methods.

points based on their normal vector and its its distance to the growing plane.

Pu [43] adopted the planar surface growing algorithm [24] for segmenting terrestrial laser data. Many important properties of point cloud data were retrieved from the segments to recognize potential building features. Ning [15] proposed a method includes two stages as rough and detail segmentation. Rough segmentation is used to extract main objects in the scene based on the consensus of normal vector in the same plane. Detailed segmentation is used as a refined process to extract finer information for object components. The work of Dorninger [16] reduced the time complexity by using a sequential implementation of the clustering algorithm. This method segments the original points by hierarchical clustering and coarse contour information.

Seeded-region approaches are highly dependent on selected seed points. Inaccurate choosing seed points will affect the segmentation process and can cause under or over segmentation. Choosing seed points as well as controlling the growing process is time consuming. The segmented results could be sensitive to the chosen compatibility thresholds. Another difficulty is to decide whether to add points in a given region, since the decision is done locally which is susceptible to noise.

Unseeded-region methods, on the contrary, base on the top-down approach. First, all points are grouped into one region. Then the subdivision process starts to divide it into smaller regions. As long as a chosen figure of merit for fitting is higher than a threshold, region subdivision is continued. Chen [8] used this method in guiding the process of clustering planar regions to reconstruct complete geometry of architectural buildings. This work introduces a segmentation method based on confidence rate of the local area to be planar. A limitation of this method is it may have over segmentation and it does not perform well when segment other objects such as trees.

The main difficulty of unseeded-region methods are to decide where and how to subdivide. Another limitation of these methods is they require a large amount of a prior knowledge (e.g., object models, number of regions, etc.) which are usually unknown in complex scenes.

C. Attributes based methods

Attributes based methods are robust approaches based on clustering attributes of point cloud data. These methods include two separate steps. The first step is attribute computation, in the second step, point clouds will be clustered based on the computed attributes. The clustering methods offer flexibility in accommodating spatial relation and attributes to incorporate different cues into the segmentation process. A limitation of these approaches is they are highly dependent on the quality of derived attributes. The attributes of point cloud data should be computed precisely to produce the best separation among different classes.

Biosca [28] introduced a new strategy for segmentation of a terrestrial laser point clouds by using unsupervised clustering approach and fuzzy algorithms. This method adapts parameters of fuzzy algorithms to use in combination with a cluster merging method. The result of this method are shown to be promising but it relies on choosing correct parameters and is time consuming.

Filin [34] proposed a methodology for clustering laser data surfaces. This approach uses surface texture measures and does not require limiting the data volume that is processed or defining windows to identify surface texture in the data. It can cope with the varying point density and operates on the laser points directly without rasterization. An improvement of this approach can be found in [23]. This work proposed a segmentation method based cluster analysis in a feature space. In this method, the normal vectors are derived using a neighborhood system called slope adaptive. Neighborhood among the measured points is defined using attributes of point cloud data, e.g., distance, point density, and horizontal or vertical point distribution. Then, the slopes of the normal vector in each directions and height difference between the point and its neighbourhood are used as the clustering attributes. This method can eliminate the influence of outliers or noise.

Vosselman [25] used 3D version of the well known Hough transform for segmentation of planar surfaces in a laser point cloud data. In this method, each point is redefined as a plane in the 3D attribute space. Thought experiments, authors showed that this method successfully extracts planar faces from the irregularly distributed point clouds, but it sometimes leads to over segmentation results.

Attributes based methods are the robust approach for grouping points into homogeneous regions. Their results are flexible and accurate. However, these methods rely on the definition of neighbourhood between points and the point density of point cloud data. Another limitation of these methods is time consuming when dealing with multidimensional attributes for a massive amount of input points.

D. Model based methods

Model based methods use geometric primitive shapes (e.g. sphere, cone, plane, and cylinder) for grouping points. The points which have the same mathematical representation are grouped as one segment. Fischer [5] introduced a well known algorithm called RANSAC (RANdom SAmple Consensus). RANSAC is a robust model and is used to detect mathematical features like straight lines, circles, etc. This method is now the state of the art for model fitting. In 3D point cloud segmentation, many subsequent works have inherited this initial algorithm.

Schnabel et al. [30] proposed an algorithm that used RANSAC for segmenting both mesh and point cloud data. This method can automatically detect basic shapes in unorganized point clouds, it includes speed optimization step while still maintains the accuracy of the result. This method is robust with outliers in point cloud data or even with high degree of noise. A drawback of this method is it has to scales well to the size of the input point clouds and the size of the shapes within the data.

To expand the restriction of primitive shapes, Gelfand et al. presented in [42] a method to detect slippable shapes. Slippable shapes are defined as rotationally and translationally symmetrical shapes and include: sphere, helix, plane, cylinder, linear extrusions, and surfaces of revolution. This idea can be used to segment point cloud data contain complex shape structure by merging initial slippable surfaces. However, its accuracy relies on the selection of the size of the initial patches, which is hard to determine.

Tarsha-Kurdi [17] compared RANSAC and 3D Hough transform for automatically detect roof planes from point cloud laser data. Despite the limitation encountered in both methods, RANSAC is more efficient in both segmented results and running time. It can process a large amount of input data in negligible time. In the other hand, 3D Hough transform is slower and more sensitive to the segmentation parameters values.

The work by Li et al. [33] presented an algorithm for globally consolidating the results obtained by the RANSAC method. In this approach, RANSAC is used for local fitting of primitives. The global coupling corrects the primitives obtained in the local RANSAC stage, and brings them to precise global alignment. This technique could be used to refine the parameters of the fitted primitives when segmenting point clouds.

Model based methods have purely mathematical principle. They are fast and robust with outliers. The main limitation of these methods is their inaccuracy when dealing with different point cloud sources.

E. Graph based methods

Graph based methods consider the point clouds in terms of a graph. A simple model is each vertex corresponds to a point in the data and the edges connect to certain pairs of neighboring points. Graph based methods are accurate and gain popularity for robotic applications due to its efficiency. A well-known of this approach is FH algorithm [46]. This algorithm is simple, efficient, and operates like Kruskal's algorithm for finding a minimum spanning tree in a graph.

Golovinskiy [38] used k-nearest neighbours (KNN) to build a 3D graph on the point cloud. This method introduces a penalty function to encourage smooth segmentation where the foreground is weakly connected to the background, and minimize it with min-cut. This method can be run fully automatically, or interactively with a user interface but it requires prior knowledge on the location of the objects to be segmented.

In [18], Strom et al. extended graph based method to segment colored 3D laser point clouds. By using co-registered sensors, this work proposed a segment union criterion based on color and surface normals. It can successfully segment colored point clouds of both indoor and outdoor scenes. The experiment showed that it can run in real time, and is considerably more robust than segmenting either laser data alone or color image alone. The limitations of this method is it requires a complex sensors system and the segmentation results are sensitive with color information.

Many works on graph based methods are cast into a probabilistic inference model such as Conditional Random Fields (CRF) [41]. Rusu et al. [12] proposed an approach for labeling points with different geometric surface primitives using CRF. Like Nurunnabi [1], this method based on surface segmentation, it extracted feature descriptor called Fast Point Feature Histograms (FPFH) [6] to encode the local surface geometry around a point. By defining classes of 3D geometric surfaces, and making use of contextual information using CRF, this method is successfully segment and label 3D points based on their surfaces even with noisy data.

Schoenberg et al. [44] presented and algorithm to segment 3D points in dense range data generated from the fusion of a single optical camera and a laser scanner. This method uses Markov Random Field [3] to estimate a 3D point corresponding to each image pixel. Textured dense point clouds are generated from interpolating sparse laser range finder data constrained by an aligned optical image. The weights on graph are computed as a combination of Euclidean distances, pixel intensity differences and angles between surface normals estimated at each point. This method successfully segment point clouds in a complex urban environment with near real time performance.

To compare with other methods, graph based methods can segment complex scenes in point cloud data include noise or uneven density with better results. However, these methods are usually can not run in real time. Some of them may need offline training step or require special co-registered sensors and camera system.

IV. DISCUSSION

Significant work has been done to segment 3D point cloud data during the last few years. Different methods have been developed to effectively segment point clouds in real time. However, it is clear from the papers reviewed in this survey that due to many challenges of point cloud data, robust real time application is still not achieved.

In this article, we present an extensive survey of 3D point cloud segmentation. We group these methods into five categories based on their design mechanisms. However, in general, there are two basic approaches. The first approach uses purely mathematical model and geometric reasoning techniques such as region growing or model fitting, in combination with robust estimators to fit linear and non-linear models to point cloud data. This approach allows fast running time, achieves good results in simple scenario. The limitations of this approach are it is difficult to choose the size of model when fitting objects, sensitive with noise, and not working well in complex scenes. The second approach extracts 3D features from point cloud data using feature descriptor, and uses machine learning techniques to learn different classes of object types, and then use the resultant model to classify acquired data.

In complex scenes, the machine learning techniques will outperform techniques purely based on geometric reasoning. The reason is due to noise, uneven density, occlusions in point cloud data, it is very difficult to find and fit complicated geometric primitives to objects. Although machine learning techniques give better results, they are usually slow and rely on the result of feature extraction process.

An important information that has been neglected in the development of 3D point cloud segmentation algorithms is integration of contextual information. Recently, Anand [2] used contextual relations such as local visual appearance, shape cues, and geometric relationships combine with graphical model to semantic segment point clouds of indoor scenes and achieve good results. In addition, advances in machine learning techniques have made accurate classification of scene context possible. A method that takes advantage of contextual information combine with geometric reasoning or learning techniques would improve the segmentation results.

In this article, we classify and review 3D point cloud segmentation methods and give a brief review of the advantages, disadvantages of each method. Motivate by the range of applications, it is expected that the challenges of this problem will be addressed in the near future. We believe that this first survey on 3D point cloud segmentation with a rich bibliography content, can give valuable insight into this important topic and encourage new research.

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