ISPRS Journal of Photogrammetry and Remote Sensing 137 (2018) 112–133

Contents lists available at ScienceDirect

ISPRS Journal of Photogrammetry and Remote Sensing

journal homepage: www.elsevier.com/locate/isprsjprs

An efficient global energy optimization approach for robust 3D plane segmentation of point clouds

Zhen Dong [a,b], Bisheng Yang [a,*], Pingbo Hu [a], Sebastian Scherer [b,*]

[a] State Key Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing, Wuhan University, Wuhan 430079, China
[b] The Robotics Institute, Carnegie Mellon University, 5000 Forbes Ave, Pittsburgh, PA 15213, USA

ARTICLE INFO

Article history:
Received 19 July 2017
Received in revised form 6 November 2017
Accepted 16 January 2018

Keywords:
Plane segmentation
Multiscale supervoxel
Hybrid region growing
Energy optimization
Simulated annealing
Guided sampling

ABSTRACT

Automatic 3D plane segmentation is necessary for many applications including point cloud registration, building information model (BIM) reconstruction, simultaneous localization and mapping (SLAM), and point cloud compression. However, most of the existing 3D plane segmentation methods still suffer from low precision and recall, and inaccurate and incomplete boundaries, especially for low-quality point clouds collected by RGB-D sensors. To overcome these challenges, this paper formulates the plane segmentation problem as a global energy optimization because it is robust to high levels of noise and clutter. First, the proposed method divides the raw point cloud into multiscale supervoxels, and considers planar supervoxels and individual points corresponding to nonplanar supervoxels as basic units. Then, an efficient hybrid region growing algorithm is utilized to generate initial plane set by incrementally merging adjacent basic units with similar features. Next, the initial plane set is further enriched and refined in a mutually reinforcing manner under the framework of global energy optimization. Finally, the performances of the proposed method are evaluated with respect to six metrics (i.e., plane precision, plane recall, under-segmentation rate, over-segmentation rate, boundary precision, and boundary recall) on two benchmark datasets. Comprehensive experiments demonstrate that the proposed method obtained good performances both in high-quality TLS point clouds (i.e., SEMANTIC3D.NET dataset) and low-quality RGB-D point clouds (i.e., S3DIS dataset) with six metrics of (94.2%, 95.1%, 2.9%, 3.8%, 93.6%, 94.1%) and (90.4%, 91.4%, 8.2%, 7.6%, 90.8%, 91.7%) respectively.

1. Introduction

Automatic 3D plane segmentation is necessary in many applications, including point cloud registration (Dold and Brenner, 2006; Theiler and Schindler, 2012; Xiao et al., 2013a; Yang et al., 2016; Lin et al., 2017), building information model (BIM) reconstruction (Vosselman et al., 2004; Sampath and Shan, 2010; Jung et al., 2014; Oesau et al., 2014; Yan et al., 2014; Yang and Wang, 2016; Xu et al., 2017), simultaneous localization and mapping (SLAM) (Xiao et al., 2013b; Pham et al., 2016; Lenac et al., 2017), and point cloud data compression (Vaskevicius et al., 2010; Kaushik and Xiao, 2012). Three-dimensional point clouds generated by various 3D sensing technologies (e.g. 3D laser scanners, multi-view stereo techniques and RGB-D cameras) are frequently contaminated with outliers, noise, occlusion, and clutter, raising great challenges for robust and efficient plane segmentation. In the last decades, extensive studies have been done to improve the efficiency and robustness of 3D plane segmentation, which can be roughly categorized into four categories, i.e., region growing based methods (Tóvári and Pfeifer, 2005; Deschaud and Goulette, 2010; Nurunnabi et al., 2012; Xiao et al., 2013b; Yang and Dong, 2013; Vo et al., 2015), model fitting based methods (Vosselman et al., 2004; Boulaassal et al., 2007; Schnabel et al., 2007; Tarsha-Kurdi et al., 2007; Oehler et al., 2011; Chen et al., 2014; Xu et al., 2017), feature clustering-based methods (Filin, 2002; Filin and Pfeifer, 2006; Biosca and Lerma, 2008; Zhou et al., 2016; Kim et al., 2016), and global energy optimization based methods (Kim and Shan, 2011; Yan et al., 2014; Oesau et al., 2014; Wang et al., 2016; Pham et al., 2016).

1.1. Region growing based methods

Region growing based methods extract 3D planes by progressively merging adjacent points or voxels with similar features (e.g. normal vector). Tóvári and Pfeifer (2005) proposed a

* Corresponding authors.
E-mail addresses: bshyang@whu.edu.cn (B. Yang), basti@andrew.cmu.edu (S. Scherer).

https://doi.org/10.1016/j.isprsjprs.2018.01.013
0924-2716/

point-based region growing (PBRG) method that picked randomly a seed point and then merged its neighboring points if they fulfilled the predefined criteria, i.e. similar normal vector and small distance to the adjusting plane. Deschaud and Goulette (2010) presented a voxel-based region growing (VBRG) algorithm to improve the efficiency of PBRG by replacing points with voxels during region growing. Nurunnabi et al. (2012) improved the robustness of the PBRG by estimating more accurate normal vectors using fast minimum covariance determinant based robust principal component analysis approach. Xiao et al. (2013b) proposed a novel hybrid region growing algorithm (HRG) to detect planes in both structured and unstructured environments by using point and voxel as growth units. More precisely, the algorithm utilized single point and voxel as growth units for nonplanar and planar regions respectively, which were fast to compute, and yet exhibiting good accuracy. Vo et al. (2015) introduced an adaptive Octree-based region growing algorithm for the fast surface patch segmentation by incrementally grouping adjacent voxels with similar saliency feature, which was faster and able to achieve better precision, recall, and fitness scores compared with the conventional region growing method.

Region growing based methods are widely used for plane segmentation as they are easily implemented (Vo et al., 2015). However, they are not robust to noise, varying point density, and occlusion, and the segmentation quality strongly depends on the predefined growing criteria and the strategies for seeds selecting (Teboul et al., 2010).

1.2. Model fitting based methods

The most widely employed model fitting-based methods for plane segmentation are random sample consensus (RANSAC) (Fischler and Bolles, 1981) and Hough transform (HT) (Ballard, 1981). Both have been proven to successfully detect shapes in 2D as well as 3D (Schnabel et al., 2007). The RANSAC paradigm generates a number of model proposals by randomly sampling data points and then selects the model with the largest set of inliers with respect to some fixed threshold (Isack and Boykov, 2012). Many publications proposed various generalizations of RANSAC for plane segmentation. For example, Boulaassal et al. (2007) utilized RANSAC algorithm to extract planar parts of facades scanned by a terrestrial laser scanner. Chen et al. (2014) proposed an enhanced RANSAC algorithm for building roof segmentation, which significantly improved the efficiency of plane segmentation by using a novel localized sampling strategy. Schnabel et al. (2007) extended the RANSAC algorithm to detect multiple geometric primitives (i.e., planes, spheres, cylinders, cones and tori) in unorganized point clouds. Xu et al. (2015) introduced a new weighted RANSAC algorithm that combined the point-plane distance and the normal vector consistency for roof point cloud segmentation. In order to improve the efficiency of multiple geometric primitive extraction, Xu et al. (2017) first divided the point cloud into some individual segments using Locally Convex Connected Patches (LCCP) (Christoph et al., 2014), and then recognized and extracted geometric primitives from each segment using the method of Schnabel et al. (2007).

The HT algorithm maps every point into a discretized parameter space and then extracts planes by selecting those parameter space with a significant amount of votes. Vosselman et al. (2004) proposed an efficient variant of the HT for plane segmentation, which improved the efficiency and reliability of conventional HT by determining the plane parameters in two separate steps, i.e., determination of the plane normal vector and establishment of the distance from the plane to the origin. Tarsha-Kurdi et al. (2007) compared the performance of HT and RANSAC algorithms for 3D plane segmentation in terms of processing time and sensitivity to point cloud characteristics. The analytic comparison shows that RANSAC algorithm is more efficient and robust than HT algorithm. Oehler et al. (2011) presented an efficient multi-resolution approach to segment a 3D point cloud into planar components by combining HT and RANSAC algorithms. More precisely, the algorithm first detected the coplanar clusters with the HT technology then extracted connected components on these clusters and determined the best plane through RANSAC.

Although the reported RANSAC and HT approaches work very well for 3D plane segmentation on point cloud with low levels of noise and clutter, these algorithms still have some disadvantages. First, HT and RANSAC are sensitive to the selection of parameter value (i.e., the size of the cell in discretized parameter space, and the threshold for inlier). Second, the segmentation quality is sensitive to the point cloud characteristics (i.e., density, positional accuracy, and noise) (Vo et al., 2015). Moreover running RANSAC sequentially to detect multiple planes is widely known to be sub-optimal since the inaccuracies in detecting the first planes will heavily affect the subsequent planes (Pham et al., 2016).

1.3. Feature clustering-based methods

Feature clustering-based methods organize the point clouds into primitives based on certain pre-calculated local surface properties (e.g., normal vector, saliency feature). Filin (2002) employed mode-seeking algorithm based on seven-dimensional feature space (i.e., position (3), plane function (3) and height difference (1)) to cluster airborne laser scanning data into 3D planes. In a follow-up work, Filin and Pfeifer (2006) improved the quality of the computed features by utilizing a novel slope adaptive neighborhood system. Biosca and Lerma (2008) used Possibilistic C-Means (PCM) algorithm based on the similar feature space with Filin (2002) to the segmentation of planar surfaces, which could automatically determine the number of planes and improve the robustness to noise and outliers. Zhou et al. (2016) proposed a new method to extract planar features from the range image of a point cloud scanned by terrestrial laser scanning system. Similar with Filin and Pfeifer (2006), a plane was parameterized by its normal vector and the distance between the origin and the plane, then the planar parameters was segmented using the Iso cluster unsupervised classification method. Kim et al. (2016) proposed a robust and efficient segmentation methodology for segmentation of planar surfaces from airborne and terrestrial laser scanning data. Specifically, they increased the homogeneity of the laser point attributes by defining a neighborhood based on the shape of the surface and reduced the dimensions of the attribute space using the magnitude of the normal vector. In spite of the popularity and efficiency of feature clustering-based methods, they suffer the difficulty in neighborhood definition and are sensitive to noise and outliers (Yan et al., 2014).

1.4. Global energy optimization based methods

More recently, the global energy optimization based methods have been widely used to geometric primitive extraction both in the 2D image and 3D point cloud, which formulate the geometric primitive extraction as an energy optimization problem. The widespread applications of energy optimization based methods in the field of 2D image process can be found in (Yu et al., 2011; Isack and Boykov, 2012; Pham et al., 2014; Tennakoon et al., 2016). In the case of 3D point cloud process, (Kim and Shan, 2011) adopted the multiphase level set approach to segment planar roof primitives under an energy minimization formulation. In follow-up work, Yan et al. (2014) presented a global plane fitting approach for roof segmentation from lidar point clouds. They first segmented the roof into initial planes based on conventional region growing approach, and then refined the initial planes by minimizing a global energy function consisting of data cost term, smooth cost term