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Multi-scan segmentation of terrestrial laser scanning data based on normal variation analysis

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ABSTRACT

Point cloud segmentation groups points with similar attributes with respect to geometric, colormetric, radiometric, and/or other information to support Terrestrial Laser Scanning (TLS) data processing such as feature extraction, classification, modeling, analysis, and so forth. In this paper we propose a segmentation method consisting of two main steps. First, a novel feature extraction approach, NORmal VAriation ANAlysis (*Norvana*), eliminates some noise points and extracts edge points without requiring a general (and error prone) normal estimation at each point. Second, region growing groups the points on a smooth surface to obtain the segmentation result. For efficiency, both steps exploit the angular grid structure storing each TLS scan that is often neglected in many segmentation algorithms, which are primarily developed for unorganized point clouds. Additionally, unlike the existing methods exploiting the angular grid structure that can only be applied to a single scan, the proposed method is able to segment multiple registered scans simultaneously. The algorithm also takes advantage of parallel programming for efficiency. In the experiment, both qualitative and quantitative evaluations are performed through two datasets whilst the robustness and efficiency of the proposed method are analyzed and discussed.

1. Introduction

Terrestrial Laser Scanning (TLS), an effective and efficient 3D data acquisition approach utilizing Light Detection and Ranging (lidar), has been widely used in a variety of applications such as topographic mapping, engineering surveying, forest management, industrial facilities, cultural heritage, geohazard analysis, and so forth. TLS datasets can contain many millions or even billions of discrete points; hence, it can be very difficult to process or analyse each single point individually both computationally and practically. The point cloud needs to be discretised into simpler features or shapes based on common attributes to support further processing and analysis in these applications. This process, known as segmentation, groups the points with similar attributes with respect to geometric, colormetric, radiometric, and/or other information. The grouped points can be then used for feature extraction, classification, modeling, analysis, and so on.

Many segmentation approaches have been developed and tested on Airborne Laser Scanning (ALS) data. While some techniques can be applied or easily adapted to TLS data (Grilli et al., 2017), TLS has notable differences from ALS and Mobile Laser Scanning (MLS) in characteristics such as view angles, spatial resolution (and variability), and applicability for an area of interest. An object is usually scanned by TLS from several surrounding scan positions while ALS scans an object from above. Although MLS acquires the data from the side of an object similar to TLS, MLS has less flexibility because it requires accessibility for a vehicle with the MLS platform. In addition, MLS and ALS are designed to cover a large area in a short period of time, while TLS usually focuses on a smaller area, enabling more details to be captured. The spatial resolution (point density) of TLS data also varies significantly across the scene by orders of magnitudes due to the fixed (static) set up and scan pattern. Thus, with respect to data size and geometric complexity, segmentation for TLS data presents different challenges compared with ALS and MLS data. Existing segmentation approaches specific to TLS can be categorized into point cloud-based and image-based approaches. In the following sections, these approaches will be summarized.

1.1. Point cloud-based segmentation

Point cloud-based approaches segment the data primarily using 3D geometric characteristics. Most of these methods group points through either region growing or clustering technique. The

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primary difference between them is that the criteria for a region growing focuses more on the relationship between the points in a neighborhood rather than the attributes at each single point in a clustering procedure.

1.1.1. Region growing

In general, for each segment, region growing will initiate from one or more seed points manually selected or meeting a specific criterion. Then, the growing process groups the points in a neighborhood iteratively through additional criteria to determine whether to continue growing or to break. Rabbani et al. (2006) present a region growing-based method for the segmentation of smooth surfaces. A threshold of maximum residuals of plane fitting is provided to automatically seed points. The growing process is then performed with a criterion comparing the normal vector between the current point and its neighbor. To cope with both planar and pole-like objects, Habib and Lin (2016) propose a region-growing, multi-class, simultaneous segmentation procedure which initiates from the optimal seed regions selected based on the residuals of fitting a planar or pole-like feature. Belton and Lichti (2006) discuss techniques to classify a point as a surface, boundary, or edge point and perform region growing to segment the point cloud. The classification can ensure that the boundary and edge points will not be selected as seed points. Similarly, Nurunnabi et al. (2012) implement a modified Principal Component Analysis (PCA) to perform a more robust normal estimation and feature extraction for the following segmentation. In addition to the geometry of the objects such as surface roughness and curvature, Dimitrov and Golparvar-Fard (2015) present a multi-scale feature detection approach considering point density, which changes dramatically in a TLS data due to the scan pattern. Another approach to overcome the challenge of variable point density is resampling. For example, Vo et al. (2015) generate an adaptive octree to resample the data into voxels such that a region growing-based coarse segmentation can be performed first.

1.1.2. Clustering

Some segmentation methods based on clustering techniques group the points using one or more geometric attributes computed for each individual point. The attributes can be an n-dimensional feature vector, which can distinguish the points lying on different classes. For example, Vosselman et al. (2004) implement a 3D Hough transform to extract parameterized shapes such as planes, cylinders, and spheres. Similarly, Maalek et al. (2015) first extract planar features and linear features from the point cloud using PCA and then cluster the planar feature points from the plane parameters. Lari et al. (2011) utilize point density to classify the point cloud into planar and rough surfaces, where the normal of the best fitting plane at each point is used for computing the attributes. Kim et al. (2016) propose a segmentation of planar surfaces using the magnitude of normal position vector for a cylindrical neighbor, which uses two sets of best-fitting plane parameters against two origins as attributes. To segment and classify a more complex natural scene, Brodu and Lague (2012) present a multi-scale dimensionality attribute for segmentation and classification where PCA is primarily used to describe the local point distribution in different scales.

Some methods utilize pattern recognition or machine learning clustering approaches for a point cloud segmentation. Biosca and Lerma (2008) present a clustering method for segmentation where, for each point, a plane best fit to its neighbors is used for computing the feature vector including the height difference, normal direction, and projected distance against the origin. Next, Fuzzy C-Means (FCM) and Possibilistic C-Means (PCM) are utilized to group the points into segments. Yang and Dong (2013) classify the point cloud according to geometric features using support vector machines (SVMs). The classification result is segmented by defining a set of rules and can be further refined by merging the segments based on topological connectivity. Weinmann et al. (2015) propose a framework for semantic point cloud interpretation consisting of optimal neighborhood selection, feature extraction, feature selection, and supervised classification. For the supervised classification, various machine learning methods are discussed and tested in the experiment. With a similar workflow, Hackel et al. (2016) propose a more efficient method of semantic classification and demonstrate the effectiveness with both TLS and MLS data.

Some other methods resample the data into 3D voxels to organize the point cloud and simplify the computation. Aijazi et al. (2013) utilize the position, normal, color, and intensity information to assign the feature vector to each voxel, which is further used in clustering and classification. Li et al. (2017a) separate ground and non-ground voxels, cluster them based on local point density, and refine them through a merging and re-assignment process. Su et al. (2016) present a segmentation algorithm for industrial sites where an octree-based split is performed based on a graph theory analysis. The criteria of proximity, orientation, and curvature are used for a merging process. Xu et al. (2016) propose a hierarchical segmentation method that first divides the point cloud into patches and then merges over-segmented patches by setting a grouping criterion in different levels. Similar to the concept of voxels, Li et al. (2017b) utilize Normal Distribution Transform (NDT) cells to resample the data and segment the data based on RANSAC.

1.2. Image-based segmentation

An image-based segmentation method often follows these three steps: (1) projecting or structuring the TLS data into a 2D image (e.g., exploiting the angular grid structure used in acquiring a TLS scan) including single or multiple bands; (2) performing an image segmentation; and (3) mapping the segments back to the 3D point cloud data. There are two major advantages associated with image-based segmentation methods (Mahmoudabadi et al., 2016). First, processing the data in 2D is often more computationally efficient than within 3D space. Second, a substantial amount of available techniques for image processing (e.g., image segmentation and edge detection) can be potentially applied to the 2D image derived from a TLS data.

Gorte (2007) presents a segmentation algorithm using a three-band image consisting of range (defined as the projected distance along the normal direction to the scan origin), horizontal angle, and vertical angle. Then, by setting the criterion based on the range image gradients, image segmentation is performed. The results of the experiment show that it works properly on vertical planes but fails on horizontal planes. Zhou et al. (2016) improve this approach by fine-tuning the computation of the plane parameters instead of using a coarse estimation. Barnea and Filin (2013) utilize the mean-shift algorithm to segment the image with three bands based on range, normal, and color, respectively, followed by a refinement of integrating the results in different bands. Mahmoudabadi et al. (2013) implement Simple Linear Iterative Clustering for segmenting the point cloud on a panoramic image. Support Vector Machine (SVM) is utilized for categorizing the segments to multiple classes. In addition to range, normal, and color information used in the aforementioned methods, Mahmoudabadi et al. (2016) associate more information including intensity and incidence angle in the segmentation process. High Dynamic Range (HDR) imaging is utilized to minimize color inconsistencies across multiple images due to variable lighting conditions. A panoramic image map with a series of bands is generated with all of the characteristics and then segmented to

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