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Efficient terrestrial laser scan segmentation exploiting data structure

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ABSTRACT

New technologies such as lidar enable the rapid collection of massive datasets to model a 3D scene as a point cloud. However, while hardware technology continues to advance, processing 3D point clouds into informative models remains complex and time consuming. A common approach to increase processing efficiently is to segment the point cloud into smaller sections. This paper proposes a novel approach for point cloud segmentation using computer vision algorithms to analyze panoramic representations of individual laser scans. These panoramas can be quickly created using an inherent neighborhood structure that is established during the scanning process, which scans at fixed angular increments in a cylindrical or spherical coordinate system. In the proposed approach, a selected image segmentation algorithm is applied on several input layers exploiting this angular structure including laser intensity, range, normal vectors, and color information. These segments are then mapped back to the 3D point cloud so that modeling can be completed more efficiently. This approach does not depend on pre-defined mathematical models and consequently setting parameters for them. Unlike common geometrical point cloud segmentation methods, the proposed method employs the colorimetric and intensity data as another source of information. The proposed algorithm is demonstrated on several datasets encompassing variety of scenes and objects. Results show a very high perceptual (visual) level of segmentation and thereby the feasibility of the proposed algorithm. The proposed method is also more efficient compared to Random Sample Consensus (RANSAC), which is a common approach for point cloud segmentation.

1. Introduction

Lidar (Light Detection and Ranging) technology utilizes near-infrared lasers to densely sample objects within view of the scanner in 3D (Vosselman and Maas, 2010), resulting in a point cloud with X, Y, Z coordinates for each sample point. Scanners also encode the strength of the backscatter called laser intensity (i.e., signal degradation as an intensity measurement). Although there are several factors that affect the magnitude of the laser intensity value, this value can characterize reflectance of the target surface (Kaasalainen et al., 2011; Kashani et al., 2015). In addition, most scanners are equipped with digital cameras in order to provide realistic RGB (red, green, blue) color values for each scan point.

It is well accepted that lidar is a powerful tool to produce high resolution, accurate, geospatial information for 3D modeling of an environment. As a result, 3D laser scanning is used in a wide variety of applications including surveying and mapping, industrial plant management, transportation asset management, facilities management, building information modeling, crime scene investigations, coastal erosion, rockfalls, landslides, and seismic displacements, cultural heritage and geologic instigations.

The 3D point clouds and 2D RGB images from a single scan can exceed millions of elemental units; however, these data do not contain semantic meaning (i.e., a point or pixel is not tagged with an object/surface identifier of what it represents). In many applications, a relatively small portion of the data are actually needed for mapping, modeling, and object extraction. A fundamental step in simplifying data processing and removing redundant information is segmentation (Vosselman and Maas, 2010). In more advanced processes, segmented points can then be classified (e.g., provided with semantic meaning) based on characteristics.

As will be briefly described in the next section, common methods for 3D laser point cloud segmentation require considerable manual labor, using mostly geometric-based approaches with extensive complexity and limited accuracy. Further, many of these procedures tend to fail or require significant manual intervention when faced with real world datasets containing many different kinds of objects and noise. Uneven distribution of points in 3D space and varying scale within the data also present challenges.

A key solution for this problem is utilizing the point cloud structure generated in the scanning process, producing a panorama,

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which is a 2D projection of the cylindrical or spherical coordinate system used by the scanner (Olsen et al., 2010; Barnea et al., 2007, Barnea and Filin, 2008a,b, 2012). Converting 3D lidar point clouds into these 2D panoramic image maps (PIMPs) enables one to apply available image processing and computer vision algorithms developed for 2D images. There are several algorithms successfully implemented for operating on 2D images (Szeliski, 2010) that have yet to be exploited for use with lidar data. Upon segmentation and analysis, the processed PIMPs then can be easily mapped back into 3D space, resulting in a segmented point cloud.

Measured laser intensity values are a good descriptor for the characteristics of the scanned objects. These values are mainly affected by intrinsic and extrinsic factors of the laser scanners (Kashani et al., 2015). To enhance the quality of the laser intensity PIMP, an empirical correction function is derived and applied on the raw laser intensity values.

To employ the colorimetric information, the proposed approach is applied on both PIMPs of the lidar point clouds and photographic imagery. Digital images are usually captured along with lidar typically contain three layers of information for each point as red, green and blue bands. Although these colorimetric data are generally used for visualization purposes, they have not been substantially used for point cloud segmentation purposes. Certainly, having high quality images that preserve important details can be very helpful to the process. However, a key challenge in digital image acquisition is that the illumination of most scenes vary substantially, resulting in loss of information within underexposed and overexposed regions. The High Dynamic Range (HDR) photography technique is implemented as a solution to cover the full range of light present in the scene and to have detailed digital images in dark and bright areas (Reinhard et al., 2010; Mahmoudabadi, 2015).

The primary objectives of this research can be categorized as follows:

- Develop an approach for intuitive, comprehensive point cloud segmentation in dense, large, 3D terrestrial lidar datasets by applying image processing and computer vision algorithms. Such a method can reduce computation time, improve the perceptual performance of the segmentation in the sense of visual quality, and minimize user intervention.
- Implement HDR photography to improve colorimetric data of digital images and consequently segmentation results.
- Enhance the performance of the segmentation by utilizing an empirical correction formula to correct laser intensity values for range and angle of incidence.

The organization of the paper is as follows: Section 2 provides a brief summary of the current State of the Art. Section 3 describes the methodology. Section 4 shows and discusses the results. Finally, Sections 5 presents conclusions.

2. State of the art

Point cloud segmentation and classification research is rapidly progressing for a wide variety of applications. Many novel approaches were developed for Aerial Laser Scanning (ALS), Mobile Laser Scanning (MLS), and range camera derived point clouds, which we will only briefly summarize herein as relevant. Rather, we focus this review on techniques that were developed for terrestrial laser scanning (TLS).

2.1. Geometry

Current algorithms in the literature chiefly focus on segmenting laser scanner point clouds (typically from airborne platforms) into planar regions or ground points. These are logically the most common due to the easy determination, modeling, and frequency of planar surfaces in urban environments. However, because these approaches operate in 3D space, they are computationally costly and often require the use of finely-tuned parameters, which can be laborious when applied to broader and larger datasets. There are also a variety of geometric methods for ground-filtering and vegetation removal (see Vosselman and Maas (2010) for an overview of approaches). These procedures typically operate using the fundamental algorithms of Random Sample Consensus (RANSAC) (Fischler and Bolles, 1981), Hough transforms, surface or region growing (based on proximity, slope, curvature, and surface normal) from a seed location (Rabbani et al., 2006), finding discontinuities (Wang and Shan, 2009) in the point cloud, a k-means clustering approach (Chehata et al., 2008), voxelation (Douillard et al., 2011) or using fuzzy parameters in relative height differentials (Biosca and Lerma, 2008). The RANSAC algorithm randomly and iteratively selects minimal sets (smallest number of samples required to uniquely define a model) to find the optimal parameters to fit a candidate mathematical model. Then, the parameters are evaluated to determine the consensus for the point set for the best fit to the model. It is a fairly robust approach to outliers.

In Pu et al. (2006) a simple planar surface growing algorithm is used to extract building features (walls, windows, and doors) from terrestrial laser scanned data using properties such as size, position, direction, and topology for each planar segment. Moussa and El-Sheimy (2010) consider the size of the patch to distinguish between buildings and vegetation. Lin and You (2006) first compute the normal vector for each point by tensor-voting, followed by classification through a cluster density method based on similar normal vector directions.

Gorte (2007) presents a plane segmentation approach for terrestrial lasers scans that works directly on a range image representation of the scan. Calculating image gradients as the rate of change in the distance that is observed between adjacent pixels (which represent measurements) helps characterize a plane in 3D space. Regions of adjacent pixels with similar gradients are grouped into same segment by a region-growing image segmentation.

Although primarily developed for robotics, the Point Cloud Library (PCL) (Rusu and Cousins, 2011) is a recent, powerful, open source library for segmentation through extraction of geometric primitives (planes, cylinders), laser intensity, normal vectors as well as raw RGB color, if available.

Serna and Marcotegui (2014) segment connected objects on a created digital terrain model (DTM) from 3D point clouds. Next, a support vector machine (SVM) classifies the objects based on several geometrical and contextual features. Finally, the label and class images are reprojected to the 3D point cloud. The approach was tested on benchmark MLS and ALS databases from Paris (France) and Ohio (USA). Weinmann et al. (2015) introduce a novel framework involving four successive components as (i) neighborhood selection, (ii) feature extraction, (iii) feature selection, and (iv) classification.

The aforementioned approaches have shown successful results. Nonetheless, challenges arise when using these approaches with TLS data. First, a scale parameter is required for neighborhood selection, which can vary significantly throughout a TLS point cloud due to substantial point density differences. Second, these methods only consider geometric information and do not consider intensity and photographic information. Third, supervised classification requires training features, which can be prone to bias and needs a balanced distribution of training examples per class for training process, which may not be realistic in a scene. Finally, many algorithms have been developed for small datasets (<5 million points) and have difficulty scaling up to extract objects of interested in larger datasets. With current TLS systems, it is common to have more than 20 million points per each scan.