



National Authority for Remote Sensing and Space Sciences
The Egyptian Journal of Remote Sensing and Space Sciences

www.elsevier.com/locate/ejrs
 www.sciencedirect.com



RESEARCH PAPER

Segmentation based building detection approach from LiDAR point cloud

Anandakumar M. Ramiya^{a,*}, Rama Rao Nidamanuri^a, Ramakrishnan Krishnan^b

^a Department of Earth and Space Sciences, Indian Institute of Space Science and Technology, Department of Space, Thiruvananthapuram, Kerala, India

^b Amrita Vishwa Vidyapeetham, Coimbatore, India

Received 19 January 2016; revised 1 April 2016; accepted 4 April 2016

KEYWORDS

LiDAR;
 Remote sensing;
 Building detection;
 Segmentation;
 PCL

Abstract Accurate building detection and reconstruction is an important challenge posed to the remote sensing community dealing with LiDAR point cloud. The inherent geometric nature of LiDAR point cloud provides a new dimension to the remote sensing data which can be used to produce accurate 3D building models at relatively less time compared to traditional photogrammetry based 3D reconstruction methods. 3D segmentation is a key step to bring out the implicit geometrical information from the LiDAR point cloud. This research proposes to use open source point cloud library (PCL) for 3D segmentation of LiDAR point cloud and presents a novel histogram based methodology to separate the building clusters from the non building clusters. The proposed methodology has been applied on two different airborne LiDAR datasets acquired over part of urban region around Niagara Falls, Canada and southern Washington, USA. An overall building detection accuracy of 100% and 82% respectively is achieved for the two datasets. The performance of proposed methodology has been compared with the commercially available Terrasolid software. The results show that the buildings detected using open source point cloud library produce comparable results with the buildings detected using commercial software (buildings detection accuracy: 86.3% and 89.2% respectively for the two datasets).

© 2016 National Authority for Remote Sensing and Space Sciences. Production and hosting by Elsevier B.V. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

1. Introduction

Realistic 3D city models are gaining prominence with the dynamic growth of urban landscape (Tner, 1999). Various applications in facility management, utility management,

disaster management, noise modelling, and city planning (Biljecki et al., 2015; Sun and Salvaggio, 2013; Dadras et al., 2015) substantially benefit from the availability of 3D city models. There is an increase in the demand for street level 3D view of the urban landscape due to the commercial exploitation of 3D geospatial data based products by corporate such as Google and Apple (Anguelov et al., 2010). The traditional photogrammetry based 3D capturing technique, which requires stereo images and extensive processing to create a 3D surface, is being replaced by the rapidly growing LiDAR

* Corresponding author.

E-mail address: ramiya@iist.ac.in (A.M. Ramiya).

Peer review under responsibility of National Authority for Remote Sensing and Space Sciences.

<http://dx.doi.org/10.1016/j.ejrs.2016.04.001>

1110-9823 © 2016 National Authority for Remote Sensing and Space Sciences. Production and hosting by Elsevier B.V.

This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

remote sensing techniques for fast capture of the surface geometry (Baltasavias, 1999; Burtch, 2002). The LiDAR remote sensing is a fast and relatively cost effective means to capture and represent the realistic three dimensional structure of surface objects. LiDAR remote sensing systems record position and elevation of the target points as x, y, z coordinates for representation and storing (Baltasavias, 1999). The LiDAR points are recorded in an unorganized fashion due to the nature of the scan, requiring specific data organization and processing techniques which are significantly different from the existing image processing algorithms. The airborne LiDAR data captured over an urban setting consists of returns from both the natural (trees, bare earth) and man-made features (buildings, cars, roads, etc.). Building features identification and extraction is a key step in urban modelling.

Over the past decade, several algorithms for extraction of buildings from point cloud data have been reported by researchers (Zhang and Lin, 2012; Lari et al., 2011; Wang and Tseng, 2011a; Lafarge and Mallet, 2012). Building extraction from the point cloud involves two sequential steps, namely, filtering, and segmentation. Filtering separates the ground points from non-ground points. There are many well established filtering algorithms available such as morphological filter (Vosselman, 2000), progressive densification filter (Axellson, 2000), surface based filter (Pfeifer, 2005), and segmentation based filter (Filin and Pfeifer, 2006). Morphological filter is based on using structural element which describes the admissible height difference between a ground point and a neighbouring point as a morphological operator to separate the ground and the non-ground points. In case of progressive densification, seed points are chosen to represent the ground points and are triangulated. The ground point set is progressively densified by finding the offset distance and angle of each of the points to the triangulated surface. In contrast to the above filter, surface based filter initially assumes that all the points belong to the ground and then removes non-ground points based on the weights assigned to the points. Segmentation based filter first groups the points into segments using the local normal of each point, computed using the local neighbourhood. Segments are also created using region growing techniques. The segments are then classified into ground and non-ground based on their properties. A review of filtering algorithm by Meng et al. (2010) suggests that most of the filtering algorithms perform well for flat surfaces while producing unacceptable results for undulating terrain.

Segmentation is applied on the non-ground points to detect the various objects present in a scene. Several 3D segmentation algorithms are available to detect landscape features from 3D point cloud. Density based segmentation is based on defining a neighbourhood of radius r and all the points within the sphere of radius r are said to belong to one cluster. Euclidean clustering based segmentation is one of the examples of density based segmentation (Rusu, 2009; Ghosh and Lohani, 2011). Region growing segmentation is based on growing a set of seed points based on the criteria such as global planarity and surface smoothness (Rabbani et al., 2006). Colour based region growing method uses spectral information in addition to the geometrical information for segmentation (Ramiya et al., 2016). Incremental segmentation based on octree structured voxel space is based on establishing neighbourhood of the point cloud followed by coplanar segmentation and co-surface grouping (Wang and Tseng, 2011b). Adaptive segmentation (Lari et al.,

2011) is based on defining an adaptive cylinder depending on the point density followed by plane detection. Amongst these algorithms only the density based algorithm can detect both manmade and natural objects in a scene whereas the other algorithms are suitable only for manmade objects (planar objects). For building detection purpose, from the segments created, it is necessary to separate building segments from the non building segments. Limited literature is available on the methods of automatically separating a tree cluster from a building cluster. The existing studies are based on evaluating the fitness of the roof surface points on a plane. The clusters which satisfy these conditions are classified as building segments.

Apart from the key algorithms necessary for processing and analysis, implementation platform such as software platform is a key resource for the effective and affordable analysis of LiDAR point cloud. Commercial LiDAR processing software such as Terrasolid offers routines to automatically detect the building points from the input LiDAR point cloud. However, there is no defined method for automatically extracting buildings from a point cloud besides the lower affordability of commercial software for many researchers. Recently many open source libraries are available to process 3D data. However there is no literature available showcasing the utility of the open source library for building detection. The objective of this work is to develop and validate a building extraction methodology using open source software tool. In this research, an open source point cloud library (PCL) has been used to cluster the entire point cloud data into segments. A novel building detection algorithm is then employed to separate the building clusters from the non building clusters. The buildings extracted using the proposed method are compared with the buildings extracted from a popular commercially LiDAR processing software.

2. Methods and materials

2.1. Filtering

Filtering is an important pre-processing step which separates ground points from the non-ground points thereby reducing the data size and helping in identifying building points. The adopted filtering algorithm belongs to the category of surface based filtering. Each point was given a weight based upon the distance to the mean interpolated surface. A threshold was determined based on the distance of each point from the mean surface. Based on the threshold value, the points are classified either as ground or non-ground point.

2.2. Data structuring

Each point of the LiDAR point cloud is organized in a file in the same pattern of the sensor scan mechanism. In general, the points in LiDAR data are discrete by space and unorganized due to the nature of geometry of the scanning device and target interaction. Hence the LiDAR data do not fit to represent on a grid and have an ill defined boundary hence called as point cloud. Due to this, all the three coordinate values (X, Y, Z) are required for encoding each of the point data. The random point cloud hence becomes more difficult to work with when performing operations such as search or for performing interpolation. We organized the point cloud in a hierarchical data structuring using method kd tree method (Rusu, 2009).

Download English Version:

<https://daneshyari.com/en/article/5780172>

Download Persian Version:

<https://daneshyari.com/article/5780172>

[Daneshyari.com](https://daneshyari.com)