Advanced Engineering Informatics 34 (2017) 1–16

Contents lists available at ScienceDirect

Advanced Engineering Informatics

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

Full length article

Robust normal estimation and region growing segmentation of infrastructure 3D point cloud models

Ali Khaloo, David Lattanzi *

Department of Civil, Environmental, and Infrastructure Engineering, George Mason University, Fairfax, VA 22030, United States

ARTICLE INFO

Article history:
Received 30 March 2017
Received in revised form 10 July 2017
Accepted 11 July 2017

Keywords:
Segmentation
3D point cloud models
Robust estimation
Outliers
3D reconstruction
Computer vision
Normal estimation
3D data processing

ABSTRACT

Modern remote sensing technologies such as three-dimensional (3D) laser scanners and image-based 3D scene reconstruction are in increasing demand for applications in civil infrastructure design, maintenance, operation, and as-built construction verification. The complex nature of the 3D point clouds these technologies generate, as well as the often massive scale of the 3D data, make it inefficient and time consuming to manually analyze and manipulate point clouds, and highlights the need for automated analysis techniques. This paper presents one such technique, a new region growing algorithm for the automated segmentation of both planar and non-planar surfaces in point clouds. A core component of the algorithm is a new point normal estimation method, an essential task for many point cloud processing algorithms. The newly developed estimation method utilizes robust multivariate statistical outlier analysis for reliable normal estimation in complex 3D models, considering that these models often contain regions of varying surface roughness, a mixture of high curvature and low curvature regions, and sharp features. An adaptation of Mahalanobis distance, in which the mean vector and covariance matrix are derived from a high-breakdown multivariate location and scale estimator called Deterministic MM-estimator (DetMM) is used to find and discard outlier points prior to estimating the best local tangent plane around any point in a cloud. This approach is capable of more accurately estimating point normals located in highly curved regions or near sharp features. Thereafter, the estimated point normals serve a region growing segmentation algorithm that only requires a single input parameter, an improvement over existing methods which typically require two control parameters. The reliability and robustness of the normal estimation subroutine was compared against well-known normal estimation methods including the Minimum Volume Ellipsoid (MVE) and Minimum Covariance Determinant (MCD) estimators, along with Maximum Likelihood Sample Consensus (MLESAC). The overall region growing segmentation algorithm was then experimentally validated on several challenging 3D point clouds of real-world infrastructure systems. The results indicate that the developed approach performs more accurately and robustly in comparison with conventional region growing methods, particularly in the presence of sharp features, outliers and noise.

1. Introduction

Modern remote sensing technologies have enabled the generation of accurate three-dimensional (3D) geometric models that can be used to augment and improve condition assessment, progress tracking and documentation of civil infrastructure systems. While there are many methods for creating such 3D models, terrestrial laser scanning (TLS) is the most widely used. Photogrammetric reconstruction via the Dense Structure-from-Motion (DSfM) algorithm [1], a process that converts 2D images into 3D point clouds, is often considered as a low cost alternative to TLS systems.

Accurate and efficient processing techniques of these often massive 3D data is vital for extracting useful information. Point cloud processing algorithms can be used for applications such as automatic change detection and deformation monitoring of structures [2,3], or the generation of as-built 3D models in the form of Computer-Aided Design (CAD) [4,5] or Building Information Models (BIM) [6–8]. In many algorithms, these procedures initiate by segmenting the point cloud data into appropriate segments and then recognizing primitives from the segments to generate 3D models [9].

* Corresponding author.
E-mail addresses: akhaloo@gmu.edu (A. Khaloo), dlattanz@gmu.edu (D. Lattanzi).

http://dx.doi.org/10.1016/j.aei.2017.07.002
1474-0346/

Segmenting point clouds of civil infrastructure systems is particularly challenging, as these massive 3D data sets are noisy, sparsely populated, and tend to have uneven point distribution (local point density). Scanning noise is unavoidable and varies due to laser scanning, imaging sensors, and radiometric scanning conditions. The performance of the image-based 3D reconstructions also vary due to camera imaging parameters, camera placement, scene complexity, surface texture, environmental conditions and scene size. Furthermore, the large-scale nature of most infrastructure systems, their typically complex geometry (from sharp features to highly curved regions), and the variety of textures due to varying construction materials (from smooth to very irregular), makes the segmentation of these 3D point clouds even more challenging. Segmentation methods that are robust in light of such variability are highly desirable.

The focus of this paper is on the development and validation of a point cloud segmentation algorithm that is designed with these considerations in mind. The algorithm uses a region growing approach to isolate and segment both planar and non-planar surfaces in large scale 3D point clouds. As a first step in this larger algorithm, point normals for each point in a cloud are estimated. A new and more robust outlier detection process has been designed to improve these estimations.

2. Related work

The state of research in as-built 3D modeling of infrastructure systems and semi-automated segmentation routines were covered in comprehensive review studies by Pătrăucean et al. [8] and Son et al. [10], respectively. Previous work in this domain can be separated into studies on normal estimation and/or point cloud segmentation.

2.1. Prior work in normal estimation

Reliable estimation of the normal vector at each point in a 3D point cloud has become a fundamental step in point cloud data processing. Numerous algorithms rely on accurate normal estimation, such as point-based rendering, surface reconstruction, 3D piecewise-planar reconstruction, and 3D point cloud segmentation [11]. Therefore, methods that provide a good trade-off between computational efficiency and accuracy are essential. Normal estimation in 3D point clouds can be classified into *Voronoi/Delaunay* and *Regression* methods. The comparative study by Dey et al. [12] showed that Voronoi methods are unreliable in noisy point clouds or in clouds with variations in local density variation, making this class of methods unsuitable for civil infrastructure applications.

Regression based normal estimation was pioneered in the work by Hoppe et al. [13], as a module in their surface reconstruction algorithm. Their method estimated the normal at a point $\mathbf{p}$ by fitting a local plane under the assumption of planarity in the region of the k-nearest neighbors of a given point, using Principal Component Analysis (PCA) [14]. Due to the sensitivity of PCA to outliers and the implicit smoothness assumption, this method is sensitive to outliers and noise, and cannot handle sharp features. To avoid strong assumptions for a local 3D neighborhood and reduce the sensitivity of PCA, both Mitra et al. [15] and Wang et al. [16] suggested an adaptive neighborhood size based on an iterative scheme to find the optimal k closest 3D points. Pauly et al. [17] assigned Gaussian weights to distances between point $\mathbf{p}$ and its k-nearest neighbors. To make the normal estimation more consistent near geometric singularities, such as corners and edges, Castillo et al. [18] formulated PCA as a constrained nonlinear least squares problem (NLSQ) to assign appropriate weights to neighboring points in order to minimize the contribution of points located along discontinuities.

Recently, estimating point normals in 3D point clouds with sharp features has been studied. Li et al. [19] implemented a statistical estimator for local noise in tandem with RANdom Sample Consensus (RANSAC) [20] to make the normal estimation procedure more accurate in the presence of sharp features and planar transitions. However, their method was not efficient for large 3D point clouds with variations in local point density. In the work by Boulch and Marlet [11], a version of Randomized Hough Transform (RHT) was utilized for estimating point normals in point clouds with sharp features. For more information on regression based methods and their performance, the reader is referred to comparative studies and detailed analysis by Klasing et al. [21] and Song et al. [22].

Within civil engineering applications, it is possible to improve the performance of many normal vector-based 3D model analysis techniques such as automated crack detection [23], deformation measurement [24] and 3D as-built modeling [25,26], through a more accurate estimation of point normals.

2.2. Prior work in point cloud segmentation

Segmentation algorithms can be roughly classified into three categories: *Model fitting* [27], *Clustering* [28] and *Region growing* [29] methods.

Model fitting-based methods attempt to find sets of points in the scene that fit 3D primitives. These methods generally use different adaptations of well-known algorithms such as Hough Transform (HT) and RANSAC [30]. In most cases these techniques are able to identify surfaces in cluttered scenes. However, they leverage shape primitives and are thus context specific. These methods have been used to segment point clouds of civil infrastructure systems [31,32], but tend to perform poorly in the face of large data sets or complex geometries [30] and were not considered further in this study.

Clustering-based methods aim to segment sets of points based on clustering local feature attributes of 3D point cloud data [33]. These techniques are computationally expensive for multi-dimensional features in large datasets and their performances are heavily impacted in the presence of a high proportion of outliers [28]. To date these approaches do not perform well on points placed on discontinuities (e.g. sharp features and planar transitions), since the extracted feature vectors of these points often differ from other points located on adjacent planes.

Region growing-based methods [29] use local features extracted from a neighborhood around each point to aggregate nearby points with similar properties and segment a region of a point cloud. Rabbani et al. [34] proposed a region growing technique based on smoothness constraints to extract smoothly connected areas in unstructured 3D point clouds. This method uses surface normal vectors and approximated local curvature values (which depends on normal estimation and orientation) as measures of local geometry to determine each segment. Since the normal estimation in this approach was calculated by using the PCA-based method [13], the algorithm is susceptible to noise and sharp features within the point cloud model. In the work by Son et al. [35], the aforementioned method was implemented to automatically extract 3D points corresponding to pipelines in an industrial plant. Walsh et al. [36] also implemented this algorithm to segment point clouds of small structural elements. In both of these studies, the targeted 3D scanned data was relatively "noise-free" and without any major challenges such as missing data due to occlusion or significant variability in surface roughness and curvature. Inspired by [34], Dimitrov and Golparvar-Fard [9] introduced a region growing segmentation for building point clouds that