Automation in Construction 58 (2015) 28–37

Contents lists available at ScienceDirect

Automation in Construction

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

Mobile Laser Scanner data for automatic surface detection based on line arrangement

C. Cabo *, S. García Cortés, C. Ordoñez

Department of Mining Exploitation, University of Oviedo, 33004 Oviedo, Spain

ARTICLE INFO

Article history:
Received 27 February 2015
Received in revised form 14 May 2015
Accepted 11 July 2015
Available online 25 July 2015

Keywords:
MLS (Mobile Laser Scanning)
Surface detection
Point cloud
Algorithm

ABSTRACT

An algorithm for automatic detection of planar and quasi-planar surfaces from Mobile Laser Scanning (MLS) data is proposed. The method uses line clouds for efficient data reduction of point clouds from MLS. The singular geometry of the MLS data on planar surfaces is used to transform the original point cloud into a more structured line cloud, which allows the simplification of the initial data and identification of surfaces by grouping lines. From each profile in the original dataset, strings of aligned points are identified, and a line cloud is defined by the endpoints of these strings. Lines are subsequently grouped following a set of parallelism, proximity and merging rules. The algorithm was tested using an urban dataset, and validated on 27 surfaces, by assessing the correctness and completeness of the point and line grouping. Correctness was, in all the surfaces, higher than 99%, and completeness was 90% on average.

1. Introduction

Laser scanning surveying techniques have been widely and increasingly used in many fields (such as forestry, or road and urban planning), in the last few decades [1–4]. The use of these techniques, typically produces a 3D point cloud, whose density, accuracy and spatial point distribution may significantly vary, depending on the platforms or surveying devices used.

From the early 90s the use of ALS (Airborne Laser Scanning) became widespread, as it provides spatial information of vast areas in a short period of time, with an adequate point density and accuracy for large object detection and extraction [5,6]. Later, the first Terrestrial Laser Scanners (TLS) appeared. They provide, in general, more accurate and dense point clouds than ALS, but they have some spatial limitations produced by their static nature, such as occlusions, or higher spatial heterogeneity within the point cloud. The data from ALS systems is usually obtained from an almost-nadiral perspective, which confers to the ALS point clouds a homogeneity that TLS data lacks [7]. However, for the same reason, and contrary to ALS, TLS systems are often able to register points on vertical surfaces.

In the 2000s, the first commercial Mobile Laser Scanners (MLS) arose [8–10]. These systems usually consist in (i) one or more LiDAR (Light Detection and Ranging) sensors, (ii) an IMU (Inertial Measurement Unit), and (iii) a GNSS (Global Navigation Satellite System) device, all of them deployed on a van or another type of vehicle [11–13]. MLS are able to avoid some of the said drawbacks of ALS and TLS systems: (i) point accuracy and density can be significantly higher than those of ALSs, (ii) point clouds often follow a certain pattern (i.e. produced by the movement of the sensors and the fixed relative perspective from the MLS vehicle), or the fact that (iii) some occlusions are avoided by using more than one sensor [14–17]. Nevertheless, MLS systems have some disadvantages and limitations. For instance: (i) point accuracy relies on the GNSS and the IMU, thus it is usually lower than that obtained with TLS systems, and (ii) the accessibility of the scanning targets or areas is limited by the vehicle or platform [18–20,9]. More recently, some other devices or variations of the aforementioned systems have appeared. For example, the Finnish Geodetic Institute has developed a Personal Laser Scanner (PLS) that goes beyond some of the accessibility limitations of the MLS systems [21,9].

Feature identification through visual recognition of a point cloud from a laser scan often constitutes a relatively simple task, in the sense of using adequate visualization software that even a non-trained user would be able to identify several features in the point cloud, when there is a prior knowledge from reality, e.g. a car, a building, or a tree. Such methods are widely used in order to test the accuracy of the systems and the performance of algorithms for automatic feature extraction or segmentation from LiDAR point clouds [20,22–26]. However, detection and recognition from visual inspection is a very time and resource consuming task.

Algorithms for feature detection have arisen and evolved along with LiDAR platforms and devices. Some algorithms/methods are general and therefore susceptible of being applied to any 3D point cloud [27–30], whereas, some other methods are specific for a target geometry, a point of view, or any other particular characteristic of a platform, device, or a special setting of them [23,31–34].

One of the main targets for automatic detection algorithms from 3D point clouds is surface detection and identification, since planar or ruled

* Corresponding author at: Dept. of Mining Exploitation, C/Independencia 13, 33004 Oviedo, Spain.
E-mail address: carloscabo.uniovi@gmail.com (C. Cabo).

http://dx.doi.org/10.1016/j.autcon.2015.07.005
0926-5805/

surfaces are, together with linear and cylindrical features, the most used shapes for geometrically defining the majority of the objects represented in urban and road cartography and models [35]. Some studies have addressed algorithms and methods for surface identification and extraction from MLS data in the last few years. However, most of them analyse exclusively planar surfaces, or use plane fitting techniques for all the surfaces.

In 2011, Jochem et al. [36] published a method for the extraction of vertical facades from MLS point clouds based on the use of Hough transform. In the method, seed points are randomly selected, and using a region growing algorithm, the plane parameters are estimated. This study was focused on vertical wall detection, and the detected planes are reduced to 2D lines in a vertical projection. Neither completeness nor correctness were specifically assessed in this study, but the authors affirmed that completeness could reach 50–74%.

More recently, Fan et al. (2014) [37] used an algorithm for general man-made objects, including buildings. The original data was divided into three layers using the height above ground level (AGL). Three fixed values were set for AGL ([i]: below 2 m, [ii] between 2 and 5 m, and [iii] above 5 m), and the points within each layer were projected onto a horizontal raster. Finally, a set of rules was established in order to identify objects from the footprints in the three layers. Similar footprints in at least the first two layers were considered a possible vertical façade of a building, which was subsequently checked using its convex hull and neighbourhood. The performance of the method was analysed by checking the detection rate (70% for buildings) and a further classification of the detected features. Misdetections were due to occlusions and low point density in the horizontal layers that the algorithm set.

Although Yang and Dong [38] was specially focused on pole-like object segmentation, it addressed a method for planar surface segmentation that included the use of point intensities. Points were classified according to their attributes after a PCA (Principal Components Analysis) transformation for a further point cloud classification using SVMs (Support Vector Machines). Finally, segmentation was performed by using a set of geometric rules and a merging operator. Merging methods for planar surfaces were based on normalized cuts, taking into account Euclidean distance between patches and the angle between normal vectors. The performance of the method was analysed by evaluating the classification and segmentation precision (up to 96.8%) and recall (up to 93.4%).

Lari and Habib [39] showed algorithms aiming at identifying and segmenting planar and linear or cylindrical features/objects, taking into account local point densities. Points were classified using PCA, and subsequently clustered using plane fitting and adaptive cylinders. The detected features were finally extracted using a parameter-domain segmentation approach. The algorithm was tested using both real and simulated MLS, ALS and TLS datasets. As regards the simulated MLS data (i.e. a synthetically generated MLS point cloud), 93.3% of the planar surfaces were detected. For real test data, a threshold was established by setting an acceptable noise level (i.e. distance from each point to the fitted plane). In 45% of the surfaces, the noise level was lower than the threshold (established at 4 cm). Misdetections were due to the lack of density and PCA classification errors.

Some other studies (not specifically focused on surface extraction or MLS data processing) used the concept of 2D profiles. For instance, the algorithm shown in Sithole and Vosselman [40] used the intersections of two orthogonal sets of profile lines in order to classify ALS points into three different categories: (i) bare terrain, (ii) detached objects, and (iii) attached objects. Unconnected profile lines were obtained by applying a set of connectivity rules, for their subsequent grouping and cluster classification based on line group size, height and connectivity.

In 1994, Jian and Bunke [41] proposed a method for the segmentation of planar surfaces in range images of simple objects using line grouping (based on the work from Pavlidis and Horowitz [42]). More recently, Howarth et al. [43] used the same principles for surface extraction from image and range data.

Single scan lines from MLS data were analysed in by Lin and Hyyppä [44], using the k-segments defined by Verbeek et al. [45], for two-dimensional primitive fitting, and the use of similar methods for further three-dimensional geometrical analysis is suggested.

Lehtomäki et al. [23] suggested the concept of grouping consecutive scan lines for pole-like object detection. This study developed the idea of segmenting single scan lines, for a subsequent line grouping process based on shape and position attributes of the segments.

The objective of this work is to develop an algorithm for surface detection from MLS data, based on simple geometric principles that overcomes some of the limitations of the existing methods: (i) It must not be limited to the detection of plane surfaces. It is frequent that some of the main targets of surface detection algorithms from LiDAR data are not completely flat, e.g. some slightly curved building facades, road surfaces or walls. The proposed algorithm has to be able to deal with some non-flat surfaces (i.e. ruled and/or slightly curved surfaces). (ii) It must not be limited to vertical surfaces (as algorithms exclusively focused on vertical facades), but it has to be able to detect them, even in the cases of non-strictly-flat surfaces. (iii) It simplifies the point cloud into a smaller, meaningful and easy-to-deal-with line-based structure. This line structure is based on previous work related with 2D and scan lines profiling [41,43–45]. (iv) It has to be fully automatic, thus no training data is required, contrary to methods that use supervised classification techniques, and (v) the only data required by the algorithm are XYZ coordinates and time attribute of the original points, hence no other data, such as point intensities, are needed.

The proposed algorithm is based on an initial structured simplification and transformation of the point cloud into a line cloud, i.e. set of straight segments generated and organized from the original point cloud. The line cloud is stored in a group of vectors, with a very simple structure that avoids both duplicates and nonessential points. Lines are subsequently grouped following a set of simple geometric rules, and points and lines conforming the target surfaces are identified and labelled.

2. Methodology

MLS systems are typically based on rotating LiDAR sensors, which take measurements of points that could be grouped as lines when they hit regular surfaces. For instance (as shown in Fig. 1A) most of the existent MLS systems would create, if they were used in a cylindrical tunnel (following the directrix line), a string of points that could be interpreted as a helical line. In the same way, using the MLS system along an ideal rectangular-section tunnel or a very simply-shaped street would create a group of connected straight lines (see Fig. 1B–C). The spatial configuration of those lines depends on the setting parameters of the system, i.e. speed of the vehicle, sensor trajectory, scanner orientation, and sensor measurement and rotation rates [17,23].

Our method identifies planar or ruled surfaces from straight segments that can be extracted from the scanned profiles. Strings of points can be considered as lines (i.e. polylines whose nodes are the points from a profile). However, in general, when the laser beams hit some ruled or plane surfaces, the polylines that can be formed consist of a group of consecutive and aligned segments. These small segments, which join each point from a profile with the next one, can be grouped and, therefore, simplified by eliminating all the intermediate points, thus just keeping the first and last. In that way, all the points from the same profile and the same plane surface can be simplified and represented by a single straight segment.

Once the original point cloud is transformed into straight segments, i.e. the point cloud is transformed into a line cloud, they are grouped following parallelism and node-proximity criteria.

The process is carried out in four stages:

1. Identification of polylines in the point cloud. At this first stage, points are considered nodes of polylines and the possible gaps are identified in order to split different lines.