AUTOMATIC SEGMENTATION OF BUILDING FACADES USING TERRESTRIAL LASER DATA

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ABSTRACT:

There is an increasing interest of the scientific community in the generation of 3D facade models from terrestrial laser scanner (TLS) data. The segmentation of building facades is one of the essential tasks to be carried out in a 3D modelling process. Since in reality, majority of facade components are planar, the detection and segmentation of geometric elements like planes respond to the previous task. The RANSAC paradigm is a robust estimator and probably the most widely used in the field of computer vision to compute model parameters from a dataset containing outliers. Indeed, RANSAC algorithm is usually successful for fitting geometric primitives to experimental data like for example, 3D point clouds resulting from image matching or from airborne laser scanning. The innovative idea of this study is the application of RANSAC algorithm to TLS data, characterized by a meaningful proportion of outliers. Therefore, this paper presents an approach allowing automatic segmentation and extraction of planar parts of facades scanned by TLS. Firstly, potential planes describing planar surfaces are detected and extracted using RANSAC algorithm. Then, a quality assessment based on manually extracted planes is carried out. The obtained results are evaluated and prove that the proposed method delivers qualitatively as well as quantitatively satisfactory planar facade segments.

1. INTRODUCTION

The reconstruction of geometric 3D models is one of the most important goals of 3D modelling in urban areas. In recent years, advances in resolution and accuracy have rendered airborne laser scanners (ALS) suitable for generating Digital Surface Models (DSM) and 3D models. These data alone do not provide complete 3D models since they do not cover building facades. In this context, generation of 3D city models with both high details at ground level, and complete coverage for bird's-eye view became more and more a challenging task. On the one hand, facades are acquired at ground level using Terrestrial Laser Scanners (TLS). On the other hand, roof shapes and terrain information are deduced from a DSM produced by ALS data (Tarsha-Kurdi *et al.*, 2006).

However, if numerous approaches have been developed over the past 10 years for airborne laser data, the situation is not so bright for terrestrial laser data. This is due, among others, to the gap between the architectural 3D range scanning and an efficient use of the data by professionals (Spinelli *et al.*, 2006).

According to (Barber *et al.*, 2001; Stephan *et al.*, 2002), the way in which point cloud modelling is performed depends strongly on the aim of the study. Generally, two modelling approaches can be distinguished: approaches fitting geometric primitives and approaches based on meshing methods. The latter allows fitting unspecified objects having irregular shapes and that cannot be approximated by simple geometric primitives.

The goal of this paper is to introduce an approach allowing automatic segmentation and extraction of planar parts from facades acquired by TLS. This approach is in line with fitting geometric primitives approaches. The step of segmentation which aims to decompose facades into planar surfaces is carried out using RANSAC paradigm.

After introducing the RANSAC algorithm, the methodology used to segment and extract multiple planes describing planar surfaces is presented. Furthermore, each operation is illustrated and applied on a point cloud describing a multi-planar facade. Finally, the results are presented and evaluated in a qualitative as well as in a quantitative way.

2. RELATED WORKS

A variety of techniques applied to the classification and 3D segmentation of point clouds originally result from traditional photogrammetric, computer vision and signal processing fields (Belton and Lichti, 2006). Some of these include transformations from one space into a parameter space, like for example the Hough transform and the Gaussian sphere (Vosselman *et al.*, 2004). They try to gather common elements based on the surface parameters and surface normal information respectively. Techniques such as tensor voting (Tong *et al.*, 2004; Schuster, 2004) and region growing (Besl and Jain, 1988) have been applied to segmented data based on localised information. Morphological approaches such as medial axis and skeletonisation have also been used by introducing diffusion equations, radial basis function and grass-fire techniques (Gorte and Pfeifer, 2004; Ma *et al.*, 2003).

Related to facade segmentation collected by TLS, extended region growing algorithms are often used to extract planar surfaces (Pu and Vosselman, 2006; Stamos et al., 2006; Dold and Brenner, 2004; Lerma and Biosca, 2005). It starts by determining a seed surface (a group of nearby points that fit to a plane), and then the seed surface grows according to specific criteria. On the one hand, the proximity criterion means that only points within a certain distance to a seed surface can be added to this seed surface. On the other hand, the globally planar criterion means that a plane equation is determined after fitting a plane passing through all points located in this seed surface. Points can only be added if the perpendicular distance to the plane is below some threshold. Although it provides interesting results, the limitations of this algorithm come from the big number of thresholds needed. Also computing time is considerable when the algorithm is applied on 3D point clouds.

Another method is increasingly used to extract planar surfaces especially by fitting geometric primitives. It is the RANSAC (RANdom SAmple Consensus) paradigm, which is applied to a wide range of problems dealing with model parameters estimation. Indeed, (Bauer *et al.*, 2005) use RANSAC method to detect and extract the main facade planes. Promising results are obtained for creating plane based models for buildings, even using dense 3D point clouds. However, the 3D point cloud was not acquired by TLS, but through image matching. According to (Durupt and Taillandier, 2006), RANSAC estimation algorithm can also be used to extract planar primitives directly from cadastral limits and from a DEM (Digital Elevation Model). Through their study, it is shown that an evaluation carried out on 620 buildings in a dense urban centre provides encouraging results. Nevertheless, the algorithm has only been tested on ALS data.

Often, when one wants to compute model parameters from a dataset containing a significant proportion of outliers, many computer vision algorithms - especially algorithms including robust estimation steps - are adopted. The RANSAC algorithm is probably the most widely used robust estimator in this field (Matas *et al.*, 2002). Nevertheless it has rarely been applied on TLS data for fitting models, although affected by noise and artefact errors. Hence, it is interesting to study the performance of this algorithm in estimating model parameters in a purpose of segmenting TLS data.

3. RANSAC PARADIGM

The RANSAC paradigm is an algorithm for robust fitting which has been introduced by (Fischler and Bolles, 1981). It is one of the probabilistic voting methods known to reduce the computing time. Indeed, it was developed in order to reduce the number of necessary trials of traditional voting techniques, like Hough Transform for example. In spite of the simple structure of RANSAC algorithm, it is known to be efficient.

Firstly, subsets are randomly selected from the input data and model parameters are computed so that they fit the sample. The size of the sample depends on the mathematical model (line, plane, cylinder, sphere…) one wants to find. Typically, the size of the sample is the “smallest” number of points sufficient to determine the model parameters. For example, to find a plane in the dataset, one has to select a set of three points, since three points are required to determine the parameters of a plane (normal vector and distance of plane to origin).

In a next step, the quality of the model will be evaluated. Typically, an error tolerance determines a volume around the geometric primitive within which all compatible points must fall in. Then, a cost function computes the quality of the model, the standard one being the number of inliers, i.e. points which agree with the model within an error tolerance. But other quality criteria could be used such as a standard deviation of distances from points to model for example. Therefore, the plane containing more points is considered to be the best plane. The process terminates when the likelihood of finding a better model becomes low.
The minimum number (m) of trials needed to reach a probability (p) to find at least one good set of observations - assuming a certain percentage (w) of observations to be erroneous - is given by relation (1).

$$m = \frac{\log(1-p)}{\log(1-(1-w)^S)} \tag{1}$$

where (S) is the minimum number of points necessary to calculate the parameters of the model (in the case of a planar model, S=3). Demonstration of the equation mentioned above can be found in (Fischler and Bolles, 1981).

The next part explains the methodology used and refined in order to segment a 3D point cloud of a facade into multiple planes.

4. SEGMENTATION METHODOLOGY

The segmentation proposed in this work starts with the decomposition of a 3D point cloud into many planes. After data description, a facade segmentation algorithm based on RANSAC procedure is presented. Then the step of plane extraction is explained. It must be noted that in this context, a “segment” means a set of 3D points belonging to the same surface.

4.1 Data description

The point cloud used for testing the segmentation approach covers the facade of the Graduate School of Science and Technology (INSA) of Strasbourg. It is composed of many planar surfaces containing different elements (windows, planar wall, balconies) and characterized by different materials (concrete, pane, stone). A photograph of the facade is presented in Fig. 1.

Figure 1. Photograph of the building under study

The dataset used in this study is a point cloud acquired by a Trimble GX laser scanner. The technical specifications of this kind of TLS are depicted in Table 1. Generally, a cloud is composed of 3 dimensional points defined by their Cartesian coordinates. The point cloud used as sample contains 47710 points acquired with a horizontal and vertical resolution of 150 mm at 50 m. Other properties assigned to the points provided by the laser scanner such as colour properties are voluntarily not used in this study.

Technical specifications	
Distance accuracy	7 mm at 100 m
Position accuracy	12 mm at 100 m
Angular accuracy	60 µrad (Horizontal) 70 µrad (Vertical)
Grid Resolution over 360°	3 mm at 100 m with no restriction on number of points in a scan
Spot size	3 mm at 50 m
Speed	up to 5000 points per second

Table 1. Technical specifications of Trimble GX laser scanner.

The points captured through glass and returned by parts located behind the facade have easily been manually removed using the RealWorks Survey software (Trimble). Fig. 2 shows the point cloud of the facade presented in Fig. 1, acquired by Trimble GX.

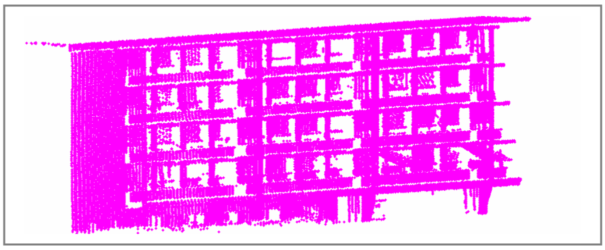


Figure 2. Point cloud describing the facade sample under study.

4.2 Facade segmentation using RANSAC algorithm

The RANSAC algorithm is used here in order to detect and extract planes describing planar parts of the facade. Practically, a plane is a row of four values [a b c d]. The first three define the unit normal vector ($a^2 + b^2 + c^2 = 1$); the fourth is the distance of the plane to the origin. Thus, all points (x, y, z) fulfilling the Equation 2 belong to the same plane.

$$a.x + b.y + c.z = d \tag{2}$$

The basic RANSAC approach is limited by the assumption that a unique model accounts for all of the data inliers. The term inliers means points which agree with the model according to an error tolerance.

However, one would like to extract all potential planes from the data. To do this, it is suggested to apply sequentially RANSAC algorithm and to remove the inliers from the original dataset every time one plane is detected. This constitutes the first adaptation of RANSAC algorithm in our context. The sequential process guaranties that each point belongs to one unique segment (plane) and that there is no intersection between two segments. Thus, a point contributes only to the fitting of the plane it belongs to.

To determine the points belonging within some tolerance to the given plane, the Euclidian distance between a point P (x,y,z) and a plane PL(a,b,c,d) is calculated (see Equation 3).

$$d(P,PL) = \left|a.x + b.y + c.z = d\right| \tag{3}$$

In reality, data acquired by terrestrial laser scanning are not immediately compatible with mathematical models. In other words, no planar walls, no straight edges, no right angles are directly provided in the digital model. Therefore, to obtain planes representing walls, one tolerance value describing the authorized thickness of a plane is imposed. Thus, the researched plane is considered to be a parallelepiped, but this is necessary at first to get meaningful segments.

In this process, different planes are detected one after the other. It is obvious that the number of planes detected depends strongly on the tolerance value chosen as input. The more this value is low, the more the number of detected planes is large. This is because each segment is a parallelepiped firstly, and tends to become a planar surface when tolerance value tends to zero. Therefore, the threshold value must be carefully chosen.

After many experiments, it turns out that the tolerance value used to get significant planes has to be set between $t = 20\ mm$ and $t = 40\ mm$. For instance, with threshold $t = 5\ mm$, the segments obtained are too numerous and not significant (Fig. 3). The main characteristic of these planes is to contain an insufficient number of points. It becomes clear that this kind of result is unusable for a later modelling process.

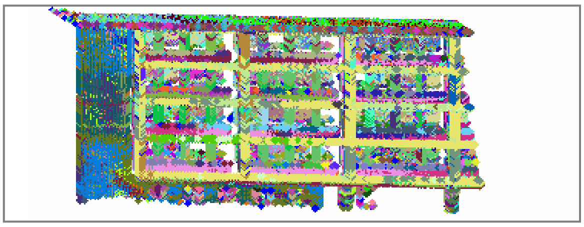


Figure 3. Detection of meaningless planes when data are segmented using $t = 5mm$. Each colour represents one plane.

On the other hand, the threshold should not overcome some tolerance (in our case $t <= 40\ mm$). Over this value, two or more different planes are considered as one unique plane (Fig. 4).

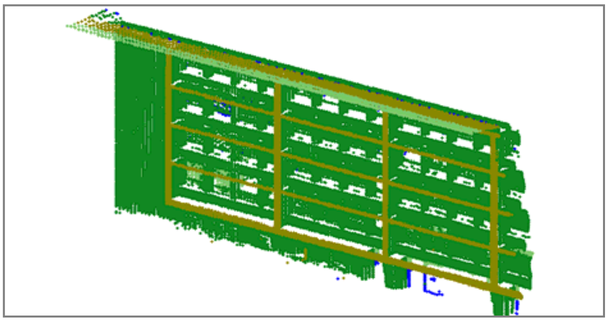


Figure 4. Detection of only two planes when data are segmented using $t = 350\ mm$.

Logically, the threshold value must be close to the thickness of the cloud. The thickness is usually generated by noise coming from the surface roughness, the object colours and the TLS resolution capacities. In the point cloud under study, it reaches about 2 to 4 cm. Thus, with $t = 40\ mm$, the expected planes are correctly detected and extracted (Fig. 5). However, it is necessary to underline that an optimal tolerance value can only be obtained in an empirical way depending heavily on the objects under investigation, on the data characteristics and the objective of the study.

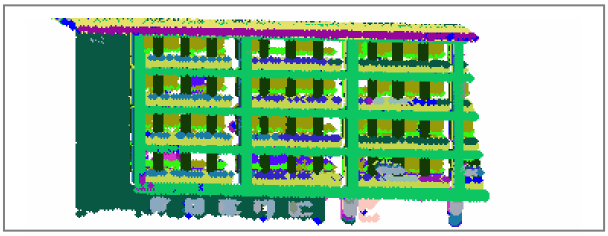


Figure 5. Successful segmentation with $t = 40\ mm$.

The minimum number of trials needed to get the best plane is given by Equation (1). Considering a value of 0.2 for w, a probability of 99% should theoretically be reached after 1000 trials.

4.3 Planes extraction

Once the main planes are determined by automatic segmentation, each plane is extracted and displayed separately. Fig. 6 shows four different planes containing points belonging to the same planar facade. The first segment is composed of points belonging to windows (Fig.-6a); the second one describes horizontal and vertical beams (Fig.-6b); the third is composed by balconies (Fig.-6c). The last one is a principal planar wall (Fig.-6d).

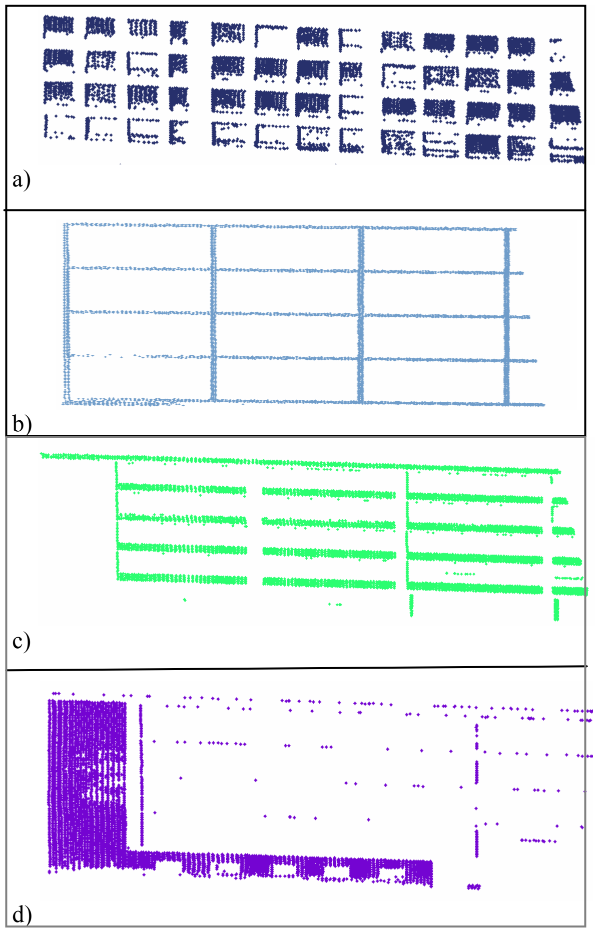


Figure 6. Four planes displayed separately; a) windows; b) beams; c) balconies; d) principal wall.

In the plane composed of windows, some windows are filled by points and others are empty. This is because either no return is measured (due to specular reflectance), or the available points refer to curtains. In principle, such holes in a point cloud can also result from shadows generated by objects located between the laser and the facade. However, this phenomenon is avoided by using several point clouds acquired from different points of view.

It can be remarked, that the extracted planes are coherent and correspond to a specific planar part of the facade. Now the results must be evaluated in detail, regarding the geometric accuracy, as well as the semantic coherency.

5. RESULTS EVALUATION

In order to evaluate the accuracy of the plane detection obtained by the presented approach, a reference model is necessary. For this purpose, a manual segmentation has been performed on the same point cloud and provided the planar surfaces composing the facade under study. These planes are then compared to their homologous, extracted automatically in the previous part. Only the results of the evaluation performed on a successful extraction (plane of Fig.-6b) and a less successful extraction (Fig.-6d) are presented in this section.

Fig. 7 presents with two colours, the same plane extracted automatically (in blue) and manually (in red). This superimposition enables to compare the results of the proposed approach to the reference data.

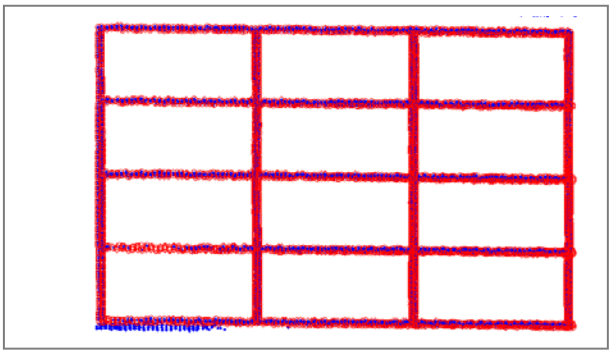


Figure 7. Superimposition of two layers: plane extracted manually (red points) and his homologous detected automatically (blue points).

A qualitative analysis of the superimpositions lead to the conclusion that both layers (automatically extracted plane against manually extracted plane) are similar. The planes extracted automatically are satisfactory, since their form and aspect are almost identical to those of the planes extracted manually.

The quantitative analysis consists in comparing two homologous planes. For this purpose, operators like intersection (∩) and difference (/) are applied on the two layers to be compared. Considering that each plane is composed of a set of points defined by their Cartesian coordinates, let's denote (A) as the set of points belonging to the automatically extracted plane and (M) the set of points belonging to the manually segmented plane.

Table 2 shows the results of the comparison of the automatically and manually segmented planes corresponding to Fig.7.

Plane	Number of points	Description
A	4658	Points extracted automatically
M	4888	Points extracted manually
A∩M	4406	Points common to both A and M planes.
A/M	482	Points of (A), not present in (M).
M/A	252	Points of (M), not present in (A).

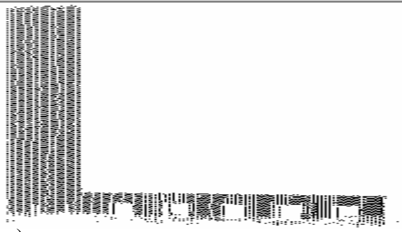
Table 2. Comparison between automatically (A) and manually (M) extracted planes.

In proportion, 4406 among 4658 points of the automatically extracted plane (A) are correctly detected. In terms of percentage, they represent 94.6 % of points. Indeed, only 252 points are lost by the proposed algorithm.
On the other hand, 482 points are in excess of the expected points. This can be explained by the fact that a plane determined by RANSAC algorithm is defined by its mathematical equation (Equation 2). Thus, all points fulfilling this equation are considered belonging to the plane, regardless of the architectural constraints describing a plane. Fig.8 shows the geometrical constraints characterizing the plane extracted in Fig.7.

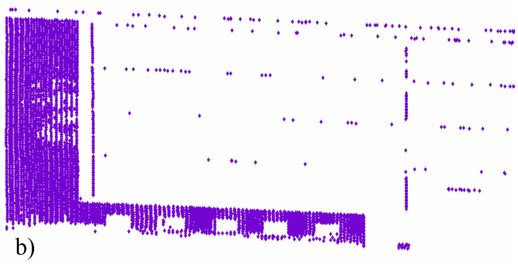
Figure 8. Part of the facade corresponding to the detected plane in Fig.7 (contours digitized in red)

Actually, manually extracted planes correspond to well-defined walls. Moreover, the architectural or semantic constraints are quite present in the manual segmentation. On the other hand, an automatically detected plane is based only on the mathematical criterion of flatness. This explains the presence of points randomly dispersed outside the expected wall (Fig.9-b), which are absent in Fig.9-a. In consequence, the percentage of points common to both planes ((A) and (M)) does not overcome 87.8% (A∩M).

This problem can be attenuated by adding constraints of topological and geometrical nature to the proposed algorithm. Indeed, from a topological point of view, a criterion of vicinity (characterized for example by a tolerated number of neighbours around each point within a given radius), enables to eliminate points lying outside the expected planar surface. From a geometrical point of view, a criterion of surface enables to keep only the significant objects. This can be done for example by converting the set of points into an image and applying image processing tools, like region growing algorithms in order to remove the meaningless points (points of (A) that are absent in (M)).



a)



b)

Figure 9. Representation of a planar wall, extracted in two ways; a) manual extraction; b) automatic extraction.

Moreover, the plane parameters estimated by RANSAC algorithm are not very accurate, since they are established based on three initial points only. They will be recomputed and adjusted, for example by a least-square fitting, to all points assigned to the detected plane.

Nevertheless, considering purely the segmentation and extraction approach proposed in this study, it can be concluded that the method is reliable. Indeed, 90% of the points composing the complete sample of the facade are correctly extracted.

6. CONCLUSION AND FUTURE WORK

The approach described in this paper aims to segment automatically and extract planar surfaces from a building facade captured by TLS. Firstly, the point cloud is segmented into several planes using sequential RANSAC algorithm. The results obtained are satisfactory, because they are produced based on the unique assertion that the best plane is the plane containing a maximum of points. Thus, considering that no additional constraint is needed, the global accuracy is better than expected. Therefore, the proposed methodology enables reliable facade segmentation with weak processing time, using TLS data. It constitutes a first and primordial step in the generation of complete 3D building models.

Future work will focus on the enhancement of segmentation operation. In order to avoid problems discussed above and increase the global and relative accuracy of the results, additional geometrical and topological constraints will be considered. Moreover, further investigations regarding the empirical parameters of RANSAC algorithm will be carried on.

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