Automatic Extraction of Planar Clusters and their Contours on Building Façades Recorded by Terrestrial Laser Scanner

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Since 3D city models need to be realistic not only from a bird's point of view, but also from a pedestrian's point of view, the interest in the generation of 3D façade models is increasing. This paper presents two successive algorithms for automatically segmenting building façades scanned by Terrestrial Laser Scanner (TLS) into planar clusters and extracting their contours. Since majority of façade components are planes, the topic of automatic extraction of planar features has been studied. The RANSAC algorithm has been chosen among numerous methods. It is a robust estimator frequently used to compute model parameters from a dataset containing outliers, as it occurs in TLS data. Nevertheless, the RANSAC algorithm has been improved in order to extract the most significant planar clusters describing the main features composing the building façades. Subsequently, a second algorithm has been developed for extracting the contours of these features. The innovative idea presented in this paper is the efficient way to detect the points composing the contours. In order to evaluate the performances of both algorithms, they have successively been applied on samples with different characteristics, i.e. densities, types of façades and size of architectural details. Finally, a quality evaluation based on the comparison of planar clusters and contours obtained manually has been carried out. The results prove that the proposed algorithms deliver qualitative as well as quantitative satisfactory results and confirm that both algorithms are reliable for the forthcoming 3D modelling of building façades.

1. INTRODUCTION

There is an obvious need for creating realistic geometric models of urban areas for many application fields, such as virtual reality, digital archaeology, urban planning or GIS data bases. Therefore, the automatic reconstruction of these kinds of 3D models is of primary importance. Recently, due to its precision, reliability, degree of automation, processing speed and easy-to-handle functionalities, Terrestrial Laser Scanner (TLS) has become one of the most suitable technologies to capture 3D models of complex and irregular building façades. Indeed, based on LIDAR technology, this instrument allows recording of 3D objects in detail and produces a set of 3D points called a point cloud. Through their practicality and versatility, this kind of instruments is widely used in the field of architectural, archaeological and environmental surveying today.

Unfortunately, although techniques for the acquisition of 3D building geometries via TLS have constantly been improved, a fully automated procedure for constructing automatically reliable 3D building models is not yet in sight. This is due essentially to the difficulties of exploring directly and automatically valuable spatial information from the huge amount of 3D data. Thus many post-processing operations must be performed before accessing to reconstruction of a reliable 3D model. One of the most important operations is the segmentation. It is often prerequisite for subdividing a huge number of points into groups of points with similar properties. To deal with this subject, it is assumed in this research work, that the most prominent features of façade components are planar. The second and following operation is the extraction of contours based on these planar clusters. In this work, a contour means the set of points composing the perimeter of a planar cluster. Generally, this operation precedes the construction of the vector model.

The goal of this paper is twofold. Firstly, it aims with the automatic segmentation of TLS data into a set of planar clusters. This is achieved by applying the adaptive RANSAC (Random Sample Consensus) algorithm. Improvements are proposed here, in order to make the algorithm more efficient. Secondly, this paper presents a new algorithm for detecting and extracting planar clusters contours.

2. RELATED WORK

Over the years a vast number of segmentation methods dealing with the extraction of surfaces from laser data have been proposed. Most segmentation techniques have been developed on airborne laser data, i.e. based on 2.5D data or image data [13; 11], but rarely on 3D data directly. Point clouds obtained by TLS are truly 3D, especially when several scans are registered and merged. Converting such point clouds into a 2D grid would cause a great loss of spatial information [1; 10].

Some efficient algorithms developed initially on airborne laser data are suitable to TLS data. For instance, the works of Pu and Vosselman [17];

Stamos *et al*. [19]; Dold and Brenner [8]; Lerma and Biosca, [12] use extended region growing algorithms for extracting planar surfaces and façade features. Also Wang and Tseng [22] and Schnabel *et al*. [18] propose an octree split-and-merge segmentation method to segment LIDAR data into clusters of 3D planes. Problems of techniques involving the merging operation are that the initial seed regions have a great influence on the final region. Moreover it is often difficult to decide if a region can further be extended, especially in case of noisy data. An extension of the basic region growing principle is the recover-and-select paradigm that has been introduced by Leonardis *et al.* [3]. In this approach several seed regions grow independently and result in potentially overlapping clusters. This extended approach often delivers a superior segmentation but still suffers from problems with noisy data.

In computer vision, two widely known methods are employed for shape extraction: the RANSAC paradigm [9] and the Hough transform [2]. Both have proved that they successfully detect geometric primitives even in presence of a high proportion of outliers. However, the Hough transform is applied mainly in 2D domain, when the number of model parameters is quite small. Tarsha-kurdi *et al*. [20] applied both algorithms for automatic detection of 3D building roof planes from airborne laser data. After an analytic comparison of both algorithms in terms of processing time and sensitivity to point cloud characteristics, this study shows that RANSAC algorithm is also more efficient in airborne laser data segmentation than a Hough transform.

On the other hand, the RANSAC algorithm is widely used as robust estimator of model parameters [14]. Moreover, the RANSAC algorithm is opposite to that conventional smoothing technique: Rather than using as much of the data as possible to obtain an initial solution and then attempting to eliminate the invalid data points, RANSAC uses as small initial data set as feasible and enlarges this set with consistent data when possible.

Its robustness to noise and outliers renders RANSAC as a suitable choice for performing shape detection on real-world scanned data. Indeed, Bauer *et al.* [6] have used RANSAC successfully to extract the main façade planes from a very dense 3D point cloud. Nevertheless, this point cloud has been obtained through image matching and was not captured by TLS. Schnabel *et al.* [18] take advantages of the favourable properties of the RANSAC paradigm for the detection of shapes such as planes, cylinders, spheres and torus in point clouds. Also Tarsha-kurdi *et al*. [4] used successfully the RANSAC algorithm for automatic detection of building roof planes from airborne laser data. Applied on façade segmentation, Boulaassal *et al.* [7] showed that a sequential application of RANSAC allows automatic segmentation and extraction of planar parts. The obtained results proved that this algorithm delivers promising results. Nevertheless, some improvements and corrections are necessary in order to make the algorithm more efficient for segmenting building façades captured by TLS.

► Figure 1. Trimble GX laser scanner.

► **Table 1. Technical specifications of Trimble GX laser scanner.**

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

3. DESCRIPTION OF TRIMBLE GX LASER SCANNER

Data sets used in this study have been acquired by a Trimble GX laser scanner (Figure 1). It uses time-of-flight measurement technology that is based upon the principle of sending out a laser pulse and measuring the time taken for the backscattering. Then the range distance between scanner and target is computed and combined with angle encoder measurements in order to provide the three-dimensional location of a point. Some technical specifications of this laser scanner are depicted in Table 1.

4. EXTRACTION OF PLANAR SURFACES USING ADAPTIVE RANSAC ALGORITHM

The adaptive RANSAC algorithm suggested by Hartley and Zisserman [5] is used here in order to detect and extract planes describing planar parts of the façade. Contrary to the basic RANSAC approach introduced by Fischler and Bolles [9] the adaptive RANSAC determines the number of samples adaptively. Indeed, the fraction of data consisting of outliers is often unknown. Therefore, the algorithm is initialized using a worst case estimate of outliers. This estimate can then be updated as larger consistent sets are found. Thereof, the fact of probing the data via the consensus sets is repeatedly applied in order to adaptively determine the number of samples. This operation is repeated for each sample, whenever a consensus set with a fraction of outliers lower than the current estimate is found. In this way, the number of iterations can be reduced considerably. Consequently, the improvement brought by adaptive RANSAC algorithm lies in the reduction of processing time, compared to the basic approach. Pseudo-code and more details about the adaptive RANSAC approach can be found in [5].

5. SEGMENTATION OF FAÇADES INTO PLANAR CLUSTERS

The adaptive RANSAC algorithm is applied to extract all potential planes in form of planar clusters. As explained in Boulaassal *et al.* [7], the algorithm is applied sequentially and removes the inliers (valid points) from the original dataset every time one plane is detected. To determine the points belonging within some tolerance to the given plane, the Euclidian distance between each point and the plane is calculated.

In reality, data acquired by TLS are not immediately compatible with mathematical models. In other words, no planar walls, no straight edges and no right angles are directly provided in the point cloud. Moreover, the raw cloud acquired by TLS has a thickness which is usually generated by noise coming from the surface roughness, the object colours, the TLS resolution capacities and the registration operation [21]. Therefore, to detect planes representing planar façade components, a tolerance value describing the authorized thickness around a plane is imposed. The planes are thus described by planar clusters having some specific thickness.

Obviously, the quality of detected planes depends strongly on the tolerance value chosen as input. Thus, the setting of such threshold must be carefully chosen. In practice the distance threshold is usually chosen empirically as it is the case in this study. However, after [5], this value may be computed if it is assumed that the measurement error is Gaussian with zero mean and a given standard deviation.

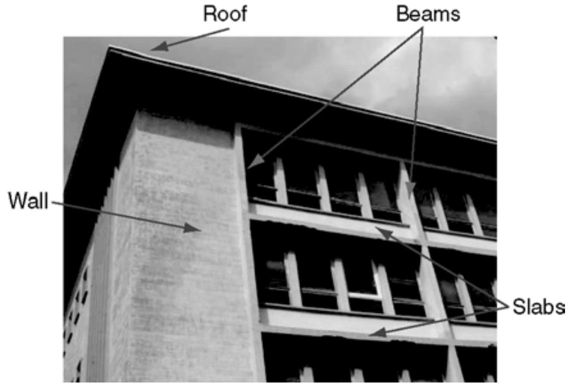
On the other side, the quality of planes is also related to the architectural complexity of the façade. In some cases, the RANSAC algorithm has some drawbacks which make it less efficient to obtain perfect results. Some of these problems are summarized in the next part.

5.1. Problem Statement

In most cases, applying the adaptive RANSAC algorithm sequentially enables detecting all potential planes (walls, slabs, beams…). But an important problem is encountered when these planes are intertwined (Figure 2). Indeed, when points of the best plane (the first one extracted) are withdrawn from the dataset, they cannot be affected, afterwards, to another plane. So if the first detected plane is not concerned by this problem, the others may be influenced and deformed by losing a considerable number of points already extracted by the first one detected. Indeed, affectation of those points to one plane or to another is depending on the chronological order in which the planes are detected.

To illustrate this problem, Figure 3 presents an example of intertwined planes extracted from point cloud describing the building façade shown in

► Figure 2. Example of a complex façade building composed of intertwined planes.



► Figure 3. Example of misclassification due to chronological plane detection.

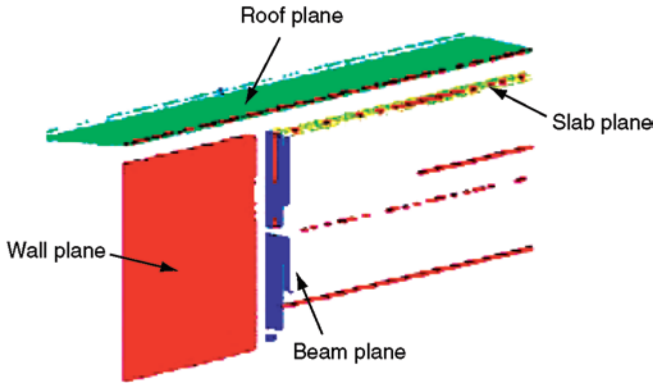


Figure 2. In this example, the plane depicting the wall plane (red one) was extracted firstly because it contains a large number of points. Consequently, it takes into account all points fulfilling within some threshold the flatness criterion, independently of any architectural constraint.

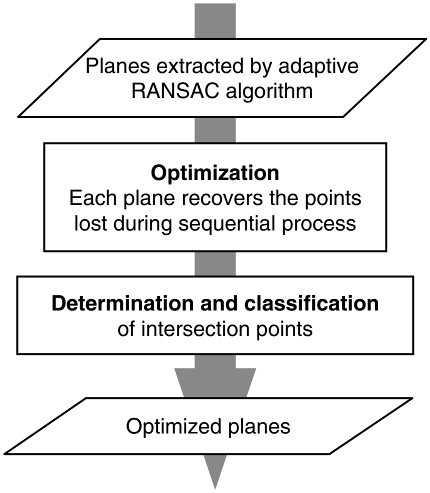
The points taken by the wall plane, although they belong practically to other planes, are drawn (in red) on the roof plane (in dark green), on the beam plane (in blue) and on the slab plane (in light green). To alleviate these defects, an algorithm aiming to optimize planes has been developed.

5.2. Algorithm for Optimization of Detected Planes

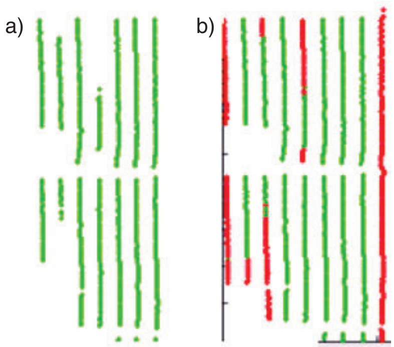
In order to improve the planes resulting from the adaptive RANSAC algorithm and to make them reliable for the next step of 3D façades modeling, an optimization is required. Figure 4 describes the workflow of the developed algorithm and is detailed in following sections.

5.3. Processing Steps for Planes Optimization

After extracting principal planes by the adaptive RANSAC algorithm applied sequentially, the parameters of each plane are known. Based on these parameters, the Euclidian distances between all points in the raw data and



◀ Figure 4. Workflow of the improvements brought to planes extracted by adaptive RANSAC algorithm.



◀ Figure 5. Detection of points belonging to a plane; a) before correction; b) after correction (red points are retrieved).

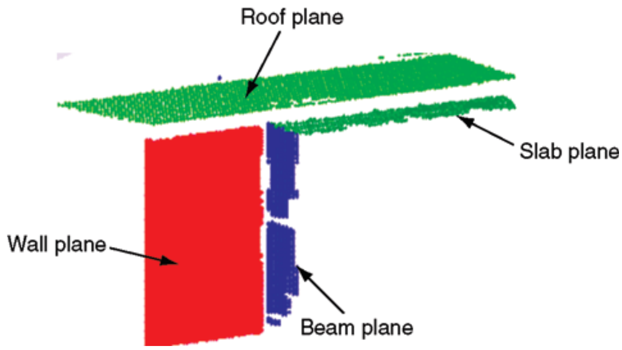
each plane are recalculated. In this way, points belonging to each plane are determined from the whole data and independently of the chronologic order in which the plane has been detected. After this improvement, previously lost points are retrieved and assigned to their corresponding plane. At this stage, it is necessary to recalculate plane parameters. Figure 5 illustrates the efficiency of the improvement. Figure 5a shows a plane before correction, i.e. with lack of points and Figure 5b after correction.

On the other hand, contrary to the planes produced sequentially by the adaptive RANSAC algorithm, the corrected ones may have common points lying for example along the intersection line between two planes. These points will be called intersection points. To be more accurate, it is necessary to detect and affect the intersection points to their right plane.

5.4. Detection and Classification of Intersection Points

Let's formulate a set of N planes by $\{PL_1; PL_2 \ldots PL_N\}$. Each plane PL_i with $i \geq 1 \ldots. N$**,** is defined by a set of 3D coplanar points and corresponds to a planar surface on building façade. The intersection between two planes PL_i and PL_j with $i \neq j$ exists if and only if they have at least one common point.

► Figure 6. Effect of the improved algorithm on the planes shown in Figure 3.



Once the intersection points determined, they must be affected to their right plane. To do this an algorithm of classification is developed. Let's denote $I = PL_i \cap PL_j$ with $i \neq j$ the intersection points. $C_i = (PL_i - I)$ is the complement of I in PL_i and $Cj = (PL_j - I)$ the complement of I in PL_j. The principle of this algorithm is based on the membership priority of each point according the proximity criterion. Indeed, the distance between each point of I and points of both complements Ci and C_j are calculated. Then the point is affected to the nearest one. This operation is repeated for all planes having intersection points. In this way, each point is assigned to its right plane. Therefore, the final planes are optimized. Since the number of points describing the intersection is relatively low, the time required for this processing remains negligible. Through this operation, not only the planes become suitable for the following 3D modelling, but also the definition of topological relationships between different planes is facilitated. Figure 6 shows the corrected planes corresponding to those depicted in Figure 3.

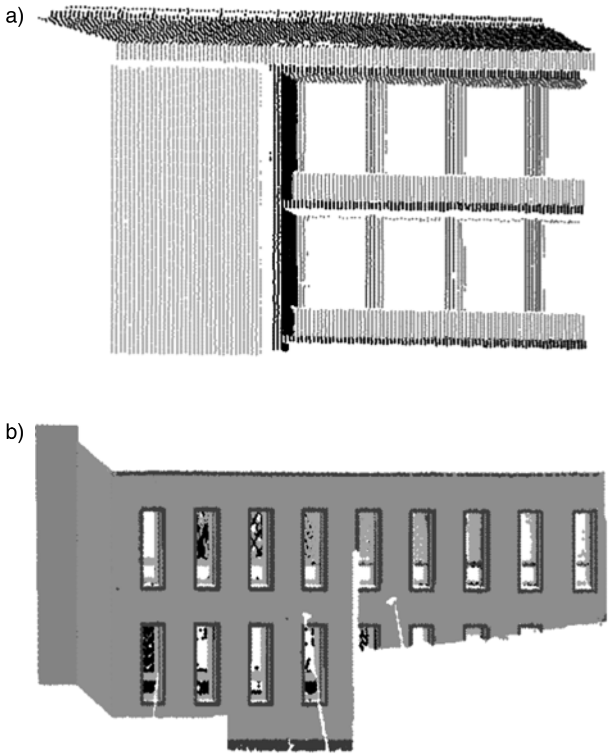
5.5. Application of the Improved Segmentation Algorithm

To test the efficiency of proposed approach, the algorithm has been applied on several point clouds, captured on different types of façades. It is important to underline that the coordinates X, Y, Z are the only information used as input in this process.

Façades considered in these samples are different regarding their architectural complexity as well as the type of their components (wall, balconies, beams, windows…etc.). Samples have also different characteristics regarding their density and the number of points composing each point cloud.

For instance, Figures 7 and 8 show segmentation results of various building façades composed of features of different architectural complexities. Each colour represents a plane describing a planar cluster.

As shown in Figures 7 and 8, the adaptive RANSAC algorithm optimized by the presented improvements provides satisfying results. The quality of segmentation may be slightly different from a data set to another depending on the characteristics of each building façade and each point cloud. Indeed, the results are better in the two first samples (Figures 7); because the façades are entirely composed by planar surfaces and they have a simple



◀ Figure 7. Results of the application of the improved segmentation algorithm on simple building façades; a) small point cloud with low density; b) bigger point cloud with higher density.

architectural description. On the other hand, the last two samples (Figure 8) are composed of more than one façade. Thus, more time is needed to handle the huge amount of points. Moreover, their architectural description is more complex. Nevertheless, all these results are widely sufficient for the forthcoming step, i.e. the extraction of feature contours.

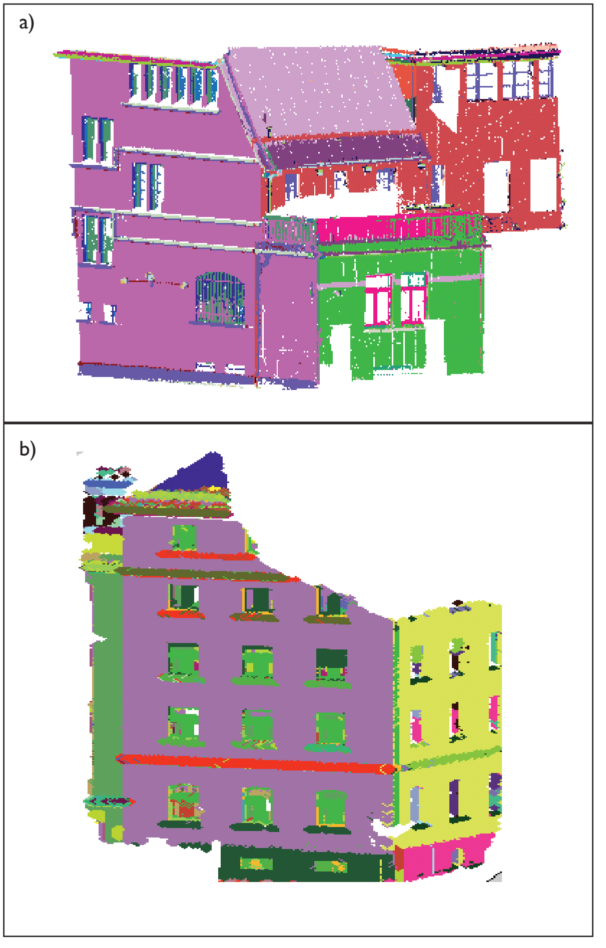
6. EXTRACTION OF CONTOUR POINTS

6.1 Principle of the Contours Extraction Algorithm

Once planar clusters are extracted by the developed segmentation approach, the extraction of their contours is carried out. To achieve this step, an efficient algorithm based on Delaunay triangulation has been developed.

Before triangulation, a new coordinate system defined in the planar cluster is determined. For this purpose, a Principal Components Analysis (PCA) is calculated based on the points of the planar cluster. The coefficients of the first two principal components define vectors that form an orthogonal basis for the plane. The third one is orthogonal to the first two, and its coefficients define the normal vector of the plane. In this principal component space, new coordinates (X_{new}, Y_{new}, Z_{new}) of points are calculated from the original ones (X_{origin}, Y_{origin}, Z_{origin}). The variance according to the third component (Z_{new}) is negligible, therefore we consider only the first two coordinates (X_{new}, Y_{new}) in the Delaunay triangulation (Figure 9).

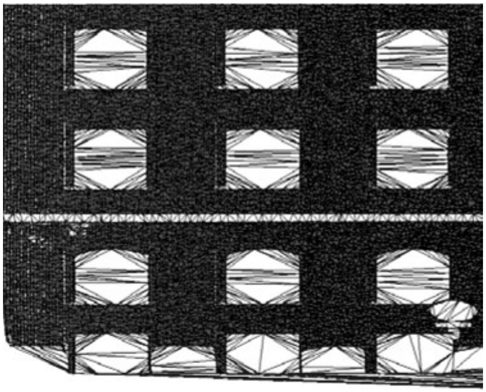
► Figure 8. Results of the application of the improved segmentation algorithm on complex building façades; a) with many edges and complex features; b) with salient features in a dense point cloud.



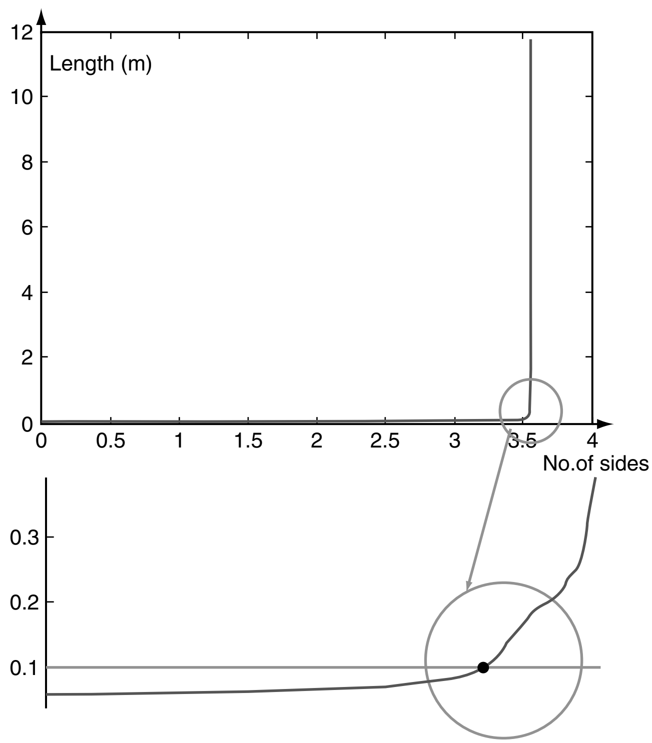
At this stage, the main new idea exploited in this algorithm is based on the hypothesis stipulating that contour points belong to the long sides of Delaunay triangles. Figure 9 shows that long sides are at the boundaries (wall contour and windows contours). The contour points are the extremities of the long sides. Therefore, lengths of all triangle sides are calculated and sorted in ascending order (Figure 10).

Two classes of side lengths can be distinguished in Figure 10. The first one contains short sides that are located on the horizontal part of the curve. The second one contains long sides that are represented by the vertical part of the curve. In reality the number of points belonging to the contour should be negligible compared to the total number of points. It is confirmed by the curve in Figure 10, since the vertical part of the curve concerns only a few sides, i.e. a few triangles.

In order to implement this hypothesis it is necessary to determine the threshold separating the two classes. Typically, this value can be determined around the point P where the curvature is changing (see zoom in Figure 10).



◀ Figure 9. Delaunay triangulation of a point cloud captured on a building façade.

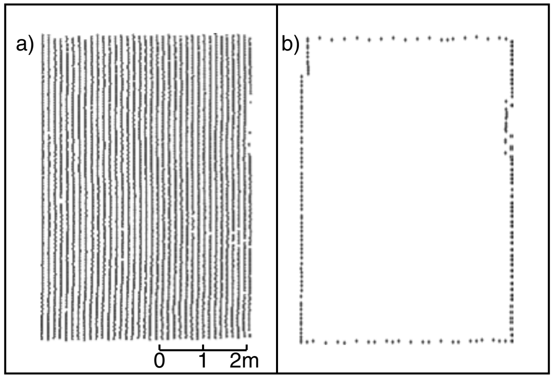


◀ Figure 10. Curve of lengths of triangle sides resulted from Delaunay triangulation and zoom on the point fixing the threshold (threshold value set at 0.1m here).

This value means that the extremities of triangle sides which length exceed 0.1m are considered as contour points.

In order to test the efficiency of proposed extraction algorithm, it has been tested over many samples. Some results are presented and discussed in following paragraph.

► Figure 11. Example of a simple plane; a) plane obtained with the segmentation algorithm; b) contour points obtained with the contours extraction algorithm.



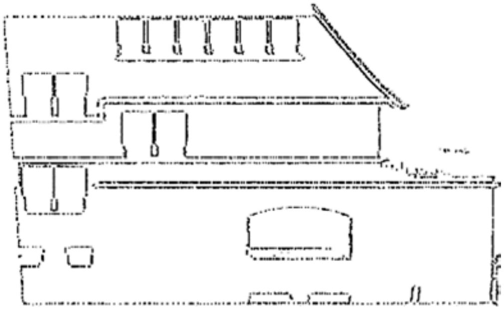
► Figure 12. Plane detected by the segmentation algorithm.

6.2. Application of the Contours Extraction Algorithm

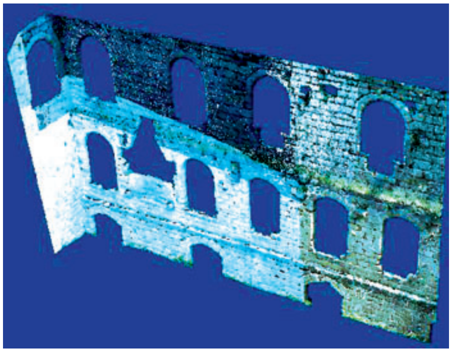
To validate the algorithm developed here, it has been applied on various planes resulting directly from the segmentation approach presented above. Planes tested are of different characteristics (point densities, total number of points, different architectural details). Figure 11 shows contour points extracted from a simple and successfully segmented plane.

One important advantage of this algorithm is to be able to extract automatically and simultaneously not only the outer but also the inner contours. Figure 13 and 16 illustrate this advantage through an example of plane containing outer contours (wall) and inner contours (holes like windows).

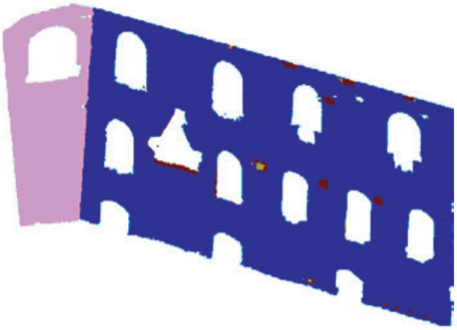
Moreover, the algorithm is able to detect the contours of architectural elements. For instance, the contours of thin elements such as transoms and mullions of windows are well extracted (Figure 13). Even in the case of destroyed façades like the walls of a medieval castle (Andlau, Alsace) the developed algorithm is able to detect windows (Figure 16). The algorithm



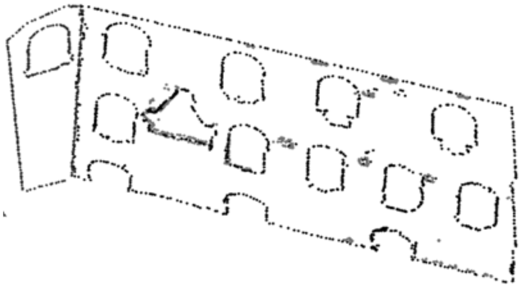
◀ Figure 13. Outer and inner contours detected by the contours extraction algorithm applied on the plane depicted in Figure 12.



◀ Figure 14. Partial point cloud of the castle of Andlau (RGB colored).



◀ Figure 15. Segmentation results for the point cloud shown in Figure 14.



◀ Figure 16. Outer and inner contour points detected by the contours extraction algorithm.

► Figure 17. Plane detection for a façade containing decorative details.

► Figure 18. Contour points extracted from the façade depicted in Figure 17.

has also been tested on planes containing decorative architectural details (Figure 17). Despite the high level of details like ornaments, it gives satisfactory results (Figure 18). Therefore, if the quality of data and their segmentation is good, the algorithm can successfully be applied simultaneously on large and small details.

Figure 19 presents an example of a building composed of adjacent façades after application of the segmentation algorithm. Figure 20 shows the contour points extracted by the extraction algorithm. Two major advantages of the developed algorithms are illustrated here.

Firstly, the two algorithms applied successively allow reducing the volume of points. Indeed, only points belonging to the contours are kept. Thus, the main structure of the façade is already emphasized (Figure 20).

Secondly, these contour points simplify the work of the user especially for the production of CAD models of a façade. Hence, manual or automatic digitizing is even easier in such a simplified cloud than in the whole cloud. Consequently, it allows an important gain of post processing time.

◀ Figure 19. Adjacent façades segmented into principal planar surfaces and features.

◀ Figure 20. Contour points of planar surfaces composing the adjacent façades depicted in Figure 19.

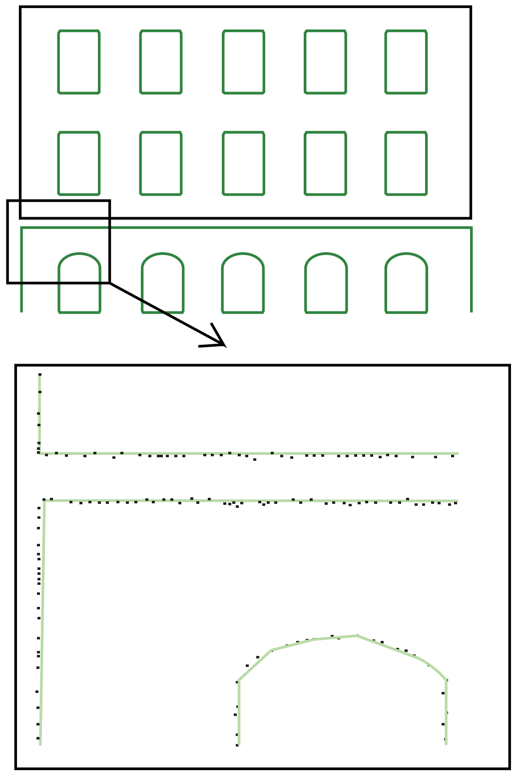
7. RESULTS EVALUATION

The evaluation of the segmentation and of the detection of contour points requires reference models. For this purpose, segmentation and an extraction of contour points have been performed manually.

Regarding the segmentation assessment, the method already published in Boulaassal *et al.* [7] has been applied. In this regard, the planar clusters extracted manually are superimposed and compared to their homologous, which extraction occurred automatically. To quantify the rate detection of the well extracted points, some indices of quality based on a set of operations are computed. In this study, 96% of points are correctly extracted. This result is satisfactory and proves that the segmentation approach is reliable.

The contour points generated by the second algorithm provide the location of the main characteristic edges of the building façade shown in Figure 20. To evaluate the quality of the contours extracted automatically, they have been superimposed on the reference contours digitized manually (Figure 21).

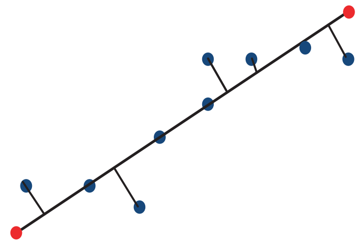
► Figure 21. Superimposition of manually digitized contours (green lines) and automatically extracted contour points (black points). The lower window shows a zoom.



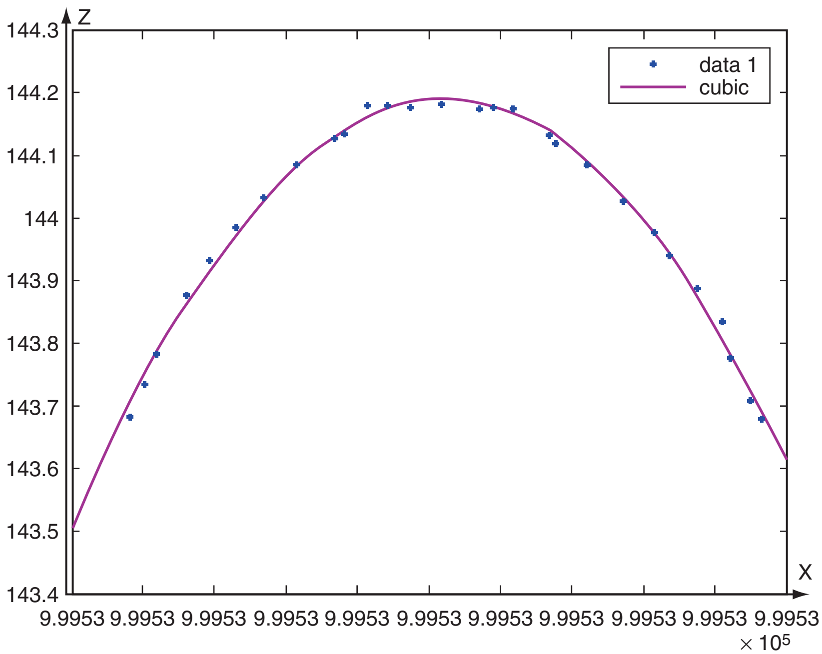
The manual digitizing is carried out by drawing straight lines and arcs in the raw point cloud. To quantify the quality of the position of contour points, distances of each point to the corresponding straight line are computed. The straight line is defined by its extremities (red points in Figure 22). Then the detection accuracy is defined as the standard deviation of distance values. In this study, the accuracy of straight contours extraction is ± 2.5 cm.

To assess the quality of the points describing arcs, a polynomial curve fitting is used. In this case, residuals are defined as the difference between the contour points (blue points) and the values that are predicted by the model (red curve) as illustrated in Figure 23. The fitting is performed using a cubic polynomial model. Thus, the extraction accuracy of arcs is about ± 3 cm.

Through the qualitative as well as the quantitative evaluation of the results, the algorithms proposed in this paper are validated. However, it is necessary to delve the evaluation process by comparing, in a next step, the vector model generated from the contour points with a reference vector model obtained by photogrammetry for instance. Thus more indices of quality will be available to support the conclusions, like the quality indices suggested by McGlone and Shufelt [15]; McKeown *et al.* [16].



◀ Figure 22. Offsets between contour points and a straight line digitized manually.



◀ Figure 23. Cubic polynomial fitting of an arc.

8. CONCLUSION AND FUTURE WORK

The work presented in this paper has reached the two objectives set at the beginning. Firstly it enables the automatic extraction of planar surfaces from building façades captured by TLS. Secondly, it achieves the extraction of contour points composing the boundary of each plane in order to be used afterwards in the 3D modelling. For this purpose two algorithms have been developed and presented in this paper. Their efficiency has been tested on several point clouds and several façade types. Their contribution to building façades has been discussed and analysed.

The first algorithm is derived from adaptive RANSAC algorithm and has been applied in a sequential mode in order to extract all potential planes and to handle efficiently the number of samples. Improvements were necessary, since several points are lost during the detection. Thus, corrective operations aiming to define valid points of each plane have been implemented. Several experiments have shown that the corrections were successful.

The second algorithm presented in this study aims with the extraction of the contours of planes resulting from the previous segmentation. This extraction algorithm relies on Delaunay triangulation. The innovative idea consists in analysing the length of the triangle sides in the whole triangulated network. This algorithm has been tested and applied to many samples with different characteristics.

The results evaluation confirmed the efficiency of both algorithm for extracting, in an automatic way, planar clusters and contour points respectively. The future work will exploit the results obtained by these two algorithms for the automatic reconstruction of planar features in building façades, i.e. by generating vector models. Therefore, the goal of automatic 3D modelling of building façades will almost be reached.

Acknowledgments

The authors would like to thank "The Region Alsace" for supporting the MAP-PAGE UMR 694 research group and specially the topic of Terrestrial Laser Scanning.

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