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AN IMPROVED SEGMENTATION APPROACH FOR PLANAR SURFACES FROM UNSTRUCTURED 3D POINT CLOUDS

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Abstract

The extraction of object features from massive unstructured point clouds with different local densities, especially in the presence of random noisy points, is not a trivial task even if that feature is a planar surface. Segmentation is the most important step in the feature extraction process. In practice, most segmentation approaches use geometrical information to segment the 3D point cloud. The features generally include the position of each point (X, Y and Z), locally estimated surface normals and residuals of best fitting surfaces; however, these features could be affected by noisy points and in consequence directly affect the segmentation results. Therefore, massive unstructured and noisy point clouds also lead to bad segmentation (over-segmentation, under-segmentation or no segmentation). While the RANSAC (random sample consensus) algorithm is effective in the presence of noise and outliers, it has two significant disadvantages, namely, its efficiency and the fact that the plane detected by RANSAC may not necessarily belong to the same object surface; that is, spurious surfaces may appear, especially in the case of parallel-gradual planar surfaces such as stairs. The innovative idea proposed in this paper is a modification for the RANSAC algorithm called Seq-NV-RANSAC. This algorithm checks the normal vector (NV) between the existing point clouds and the hypothesised RANSAC plane, which is created by three random points, under an intuitive threshold value. After extracting the first plane, this process is repeated sequentially (Seq) and automatically, until no planar surfaces can be extracted from the remaining points under the existing threshold value. This prevents the extraction of spurious surfaces, brings an improvement in quality to the computed attributes and increases the degree of automation of surface extraction. Thus the best fit is achieved for the real existing surfaces.

Keywords: feature extraction, fit to reality, normal vectors, planar surfaces, RANSAC algorithm, segmentation, terrestrial laser scanner, unstructured 3D point clouds

INTRODUCTION

MORE AND MORE CLOSE RANGE SURVEY APPLICATIONS, such as 3D modelling, as-built surveys, documentation, restoration and reconstruction of objects, require automatic processing of massive point clouds to extract surfaces of the recorded objects. Terrestrial laser scanners (TLS) are considered very efficient tools for the acquisition of large quantities of data because of their speed, giving them considerable potential for data collection for 3D modelling. But TLS data, as with all other source tools for 3D data acquisition, is provided in 3D point clouds (X, Y, Z), which are not immediately compatible with mathematical models, that is to say no planar surfaces and no straight edges are directly provided in the digital model (Filin, 2002; Boulaassal et al., 2007). The final 3D point clouds are dependent on many factors, such as the colour, roughness of different surfaces, the TLS instrument resolution and the registration step, and appear with a finite thickness for planar surfaces (that is, they are in general not flat) (Boulaassal et al., 2009). Three-dimensional unstructured point clouds can be acquired even in the case of 2·5D range images once two or more such images are registered; the resulting data loses its 2·5D character and has to be represented as an unstructured 3D point cloud (Rabbani et al., 2006). In all cases, the goal is to create a 3D digital object that best fits reality (Remondino, 2003).

The segmentation process is the essential step in obtaining surfaces, since the extraction of features of the different building elements basically depends on the accuracy of the segmentation step (Rodríguez González et al., 2007). At the same time, the accuracy of the segmentation step is strongly linked with the fitting process (Várady et al., 1997; Rabbani, 2006).

> *The relations between segmentation and fitting are like the "chicken and egg" problem, because if a priori information about the surfaces and their locations is available we can just pick the points which are within a small distance of the surface. Similarly, if we know that a certain group of pixels (points) belongs to one surface, we can easily find the type of surface they represent.* (Várady et al., 1997—page 261)

Usually a TLS acquires massive unstructured 3D point clouds (randomly distributed) with different local densities, especially in the presence of random noisy points; the spatial point distribution and the point density cannot be assumed to be fixed (Filin, 2002). Therefore, most segmentation approaches use geometrical information to segment the 3D point cloud. The features generally include the position of each point (X, Y and Z), locally estimated surface normals and residuals from the best fitting surfaces. These features result from the fitting process, which could be affected by outlier points and consequently directly affect the segmentation results. Therefore, segmentation for massive unstructured point clouds also leads to bad segmentation that may consist of:

(a) over-segmentation (one feature segmented to several segments);
(b) under-segmentation (several features segmented to one segment); and
(c) no segmentation (feature is not segmented or wrongly segmented).

As man-made structures are dominated by planar surfaces, many attempts have been made to segment planar surfaces from point clouds; unfortunately in many cases these were not acquired by TLS instruments, with most authors in this field focusing on points acquired by airborne laser scanners (ALS) (such as Gorte, 2002; Tóvári and Pfeifer, 2005) or through image matching (such as Bauer et al., 2003).

Due to its merits of quality and effectiveness, the RANSAC (random sample consensus) algorithm was introduced by Fischler and Bolles (1981) to deal with outliers with respect to common TLS data, but it has a significant disadvantage, namely, the plane detected by

RANSAC may not necessarily belong to the same object surface and spurious surfaces may result, especially in the case of parallel-gradual planar surfaces such as stairs. Therefore, a new approach is proposed based on a modification of the RANSAC algorithm called "Seq-NV-RANSAC" to extract planar surfaces directly from 3D point clouds, at the same time avoiding the spurious results obtained by RANSAC in cases of parallel-gradual planar surfaces such as stairs. This approach is designed especially for dealing with TLS data, but it can also be used for any 3D point cloud.

Related Work

The Segmentation Process

The segmentation process is generally defined as a grouping of elements such as points into one region which shares similar spatial properties (Rabbani et al., 2006; Biosca and Lerma, 2008). It is one of the main research areas in the laser scanning field, designed to introduce some level of organisation to the data before extraction of useful information (Filin and Pfeifer, 2006). It is also a very important step as a precursor to object recognition and model fitting (Rabbani, 2006). When segmentation is employed as a pre-processing step before the application of filtering algorithms, it is called segmentation-based filtering (Tóvári and Pfeifer, 2005). Therefore, the segmentation processes for planar surfaces on man-made objects can be considered as a first step in the creation of 3D model documentation with a best fit to reality directly from 3D point clouds. However, although segmentation is one of the main processing steps, it is far from being solved even for planar features (Hoover et al., 1995).

In the past decade, many algorithms have been designed to extract planar surfaces from point clouds using segmentation methods. Usually one of three distinct methods is employed for segmenting points: region growing (Hofmann et al., 2002; Dold and Brenner, 2004; Pu and Vosselman, 2006), clustering of features (Filin, 2002; Hofmann, 2004; Lerma and Biosca, 2005; Filin and Pfeifer, 2006; Biosca and Lerma, 2008) or the model fitting method (Bauer et al., 2003; Bretar and Roux, 2005; Boulaassal et al., 2007, 2009). While region-growing and feature-clustering methods are based on geometrical criteria for grouping homogeneous regions that are present in the point cloud data, the model fitting algorithms are based on fitting geometric primitive shapes.

The Region-Growing Method

The region-growing method by Besl and Jain (1988) identifies homogeneous patterns in the data but is restricted to one specific pattern (the seed element). This method assumes that there is a part of the data-set where all points within some specific distance belong to the same surface (Vosselman et al., 2004). Therefore, it can be seen as a combination of two steps: identification and then growing of the seed surface. The growing of surfaces can be based on one or more of the three criteria for accepting points into the plane: proximity of point, global planarity and surface smoothness using the normal vector. However, there is no universal criterion which is valid for every case (Biosca and Lerma, 2008).

Several extensions for surface-growing methods of segmentation have been suggested. Gorte (2002) presents a variation of a region-growing algorithm for ALS data. A triangulated irregular network (TIN) is used to describe the basic elements of the surface. The merging of triangular elements is carried out by comparing the plane equation of neighbouring triangles. Tóvári and Pfeifer (2005) proposed a segmentation method for ALS data based on region growing. They estimate the normal vector at each point using the k nearest neighbours. Then, in the growing step, the neighbouring points are added to the segment based on criteria of similarity in normal vectors, distance to the growing plane and distance to the current point. Rabbani et al. (2006) proposed a method to segment industrial scenes based on a smoothness constraint. They use local surface normal estimation and the region-growing method. They employ the residuals in a plane fitting to approximately the local surface curvature. The growing of segments is performed by using previously estimated point normals and their residuals, and then the points are added to the segment by enforcing proximity and surface smoothness criteria. Pu and Vosselman (2006) proposed an approach to automatically extract planar surfaces from TLS point clouds following the region-growing segmentation method of Vosselman et al. (2004). In this approach, several parameters need to be specified for the planar surface-growing algorithm, such as the number of seeds, the surface-growing radius and the maximum distance between surfaces. Using different values for these parameters, it is easy to obtain bad segmentation (over-, under- and/or no segmentation). The authors prefer to have over-segmentation rather than under-segmentation (Pu and Vosselman, 2006).

The region-growing method does suffer from the main and difficult disadvantage of having to define the correct seed surface, because if the definition of the seed surface is wrong (particularly in the case of large noisy data-sets) the error will grow and all processes will fail. It can thus be considered a method which is sensitive to noisy data. Also, when it is employed for segmentation of massive unstructured point clouds, it leads to bad segmentation results (over-, under- and/or no segmentation) (Pu and Vosselman, 2006). Therefore, region-growing algorithms are sometimes not very transparent and not homogeneously applied (Tarsha-Kurdi et al., 2007).

The Method Based on Clustering Features

The method based on clustering features offers a general and flexible way to identify homogeneous patterns in the data, without being restricted to one specific pattern. It can be seen as a combination of two processes—identifying patterns in the data based on attributes and grouping the data into clusters. Since clustering-of-features methods are dependent on the quality of the computed attributes, attributes should identify the properties that capture the information sought and produce the best separation among classes (Filin, 2002).

Filin (2002) presents a clustering algorithm using an unsupervised classification technique for extracting homogeneous segments in ALS data from irregularly distributed points that carry only a limited amount of information (x, y, z). The goal is to find clusters that are spatially meaningful and at the same time to avoid over-segmentation. The author defines a seven-dimensional vector for each feature point, consisting of point coordinates, the surface parameters of a plane fitted to the neighbourhood of the point and the relative height difference between the point and its neighbours. Hofmann et al. (2003) use a TIN structure, which is calculated for ALS point clouds. They present a clustering-method-based feature vector for 2D (slope and orientation) and 3D (slope, orientation and O-distance) parameters for each triangle of a TIN structure. O-distance is defined as the minimum distance of a plane that is calculated in the triangle from the origin. They mentioned in their conclusion: "Systematic errors will prevent a successful clustering, but single outliers will not affect the cluster analysis"—page 116. Neighbourhood systems (called "slope adaptive") are proposed by Filin and Pfeifer (2006) for segmentation based on cluster analysis in a feature space for ALS data. They use some parameters of the laser data (point density, measurement accuracy, and horizontal and vertical point distribution) for defining the neighbourhood among the measured points. It is clear that parameters are not matched for the present case. Biosca and Lerma (2008) proposed an unsupervised clustering approach based on fuzzy methods. Both the Fuzzy C-Means (FCM) algorithm and the Possibilistic C-Means (PCM) mode-seeking algorithm are used in combination with a similarity-driven cluster merging method.

While clustering methodology offers a general and flexible way to identify homogeneous patterns in the data, without restriction to one specific pattern, feature extraction directly from massive unstructured 3D point clouds based only on the clustering method has not proved to be practical, especially in the presence of noisy data and outliers, since computationally clustering multidimensional features for large data volumes is very expensive, and dealing with a large volume of data is an obvious requirement for point clouds from laser scanning (Sapkota, 2008). Also the method is sensitive to the noise in the data and is influenced by the definition of the neighbourhoods. Therefore, an additional robust method is needed to eliminate the noisy data and outliers, but these are essentially greedy algorithms and are very slow.

The Model Fitting Method

The model fitting method is based on fitting geometric primitive shapes, which can be represented mathematically as planar surfaces; then points are conformed by the mathematical representation that would group them as one segment. Two widely known algorithms in line with model fitting methods are RANSAC (introduced by Fischler and Bolles, 1981) and the Hough transform introduced by Hough (1962). While these two algorithms were used earlier for processing point clouds automatically, with the major aim of constructing 3D building models, an important comparison has been made by Tarsha-Kurdi et al. (2007) between the algorithms in terms of processing time and sensitivity to cloud characteristics using ALS point clouds. These authors show that despite the limitations of both algorithms, the RANSAC algorithm is still more efficient than the Hough transform. Another advantage is that its processing time is negligible even when the input data size is very large. On the other hand, the Hough transform is very sensitive to the segmentation parameter values. Therefore, the present work concentrates on the RANSAC algorithm for segmenting planar surfaces from unstructured 3D point clouds.

While the RANSAC algorithm has the great advantage of being robust, even in the presence of much noise, there are also shortcomings which should not be overlooked. The original RANSAC paradigm depends on three main steps and three threshold values:

(1) *Main steps*
  (a) Select N random points, as a sample, from the input data. The number N is the minimum number of points needed to fit the desired surface. For example, for fitting planar surfaces, $N = 3$.
  (b) Based on N, RANSAC calculates the mathematical parameters for that desired surface. For example, for fitting planar surfaces, the parameters are a, b, c and d in following equation:

$$aX + bY + cZ + d = 0 \tag{1}$$

where (a, b, c) is the normal vector for the surface and d is the perpendicular distance between that plane and the origin point.

  (c) Use the threshold values to accept points from support points (remaining points).

(2) *Threshold values*
  (a) (MaxIterNo): the maximum number of iterations.
  (b) (MinPointNo): the minimum number of accepted points, from support points, in one surface.

(c) (Tol): the tolerance value for accepted inlier points based on perpendicular distances between each point and its surface, based on the thickness of the acquired point clouds. Here inliers are those points agreeing with equation (1) with a tolerance error.

Many papers have concluded that the two distinguishing shortcomings of the RANSAC algorithm are its relative inefficiency and the spurious results with segments and/or extracted planar surfaces from different point cloud sources. Usually the authors are interested in solving the efficiency problem by trying to reduce the number of iterations and consequently reducing the processing time, such as with the adaptive RANSAC algorithm suggested by Hartley and Zisserman (2003).

In fact the efficiency for any algorithm is important; on the other hand, efficiency with the probability of getting spurious results is not useful for users. According to Sapkota (2008), "the plane detected by RANSAC may not necessarily belong to the same object surface"—page 19, meaning that spurious surfaces may result. Therefore, a practical test was carried out to evaluate the spurious results from RANSAC. Stairs provide the ideal example for parallel-gradual planar surfaces (Fig. 1). According to the results obtained by RANSAC for the segmented planar surface shown in Fig. 2, the spurious result (oblique surfaces) is obvious. Spurious results represent a serious obstacle even to extracting automatically only the planar surfaces by RANSAC. On the other hand, these results can also be considered as a clear case of bad segmentation (under-segmentation and/or no segmentation).

This problem may have happened because RANSAC accepts planar surfaces that only have the maximum number of points (MaxPointNo) from all iterations (MaxIterNo). Thus, in the case of parallel-gradual planar surfaces, the plane with (MaxPointNo) is usually the oblique surface (spurious planes).

Dorninger and Nothegger (2007) touch on the problem when they mention that "RANSAC uses the object space (i.e. point position) only and cannot take *N* additional parameters (e.g. local normals) into account"—page 193. Although Bretar and Roux (2005) proposed the Normal Driven RANSAC algorithm (ND-RANSAC) for extracting 3D planar primitives using ALS point clouds by calculating the normal vectors for each point, they only used the normal to select the random three points having the same orientation as the normal vectors. In the present case, the problems of the spurious results from RANSAC for parallel-gradual planar surfaces cannot be solved using the ND-RANSAC algorithm, since the three random points having the same orientation of their normal vectors and MaxPointNo will also be detected from the spurious plane (oblique surface) (see Fig. 2). While Boulaassal et al. (2007) showed that a sequential application of RANSAC allows automatic segmentation of planar surfaces from 3D point clouds acquired by TLS, these are not exposed to spurious results from RANSAC and use a very small point cloud (47 710 points). In order to increase RANSAC capacities for automatic roof-plane detection from ALS, Tarsha-Kurdi et al. (2008) suggest two improvements. The first is an improvement of the original data by generating a

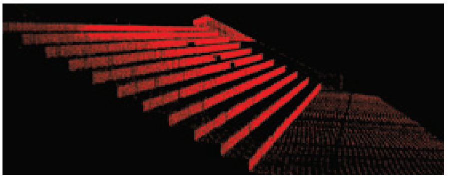
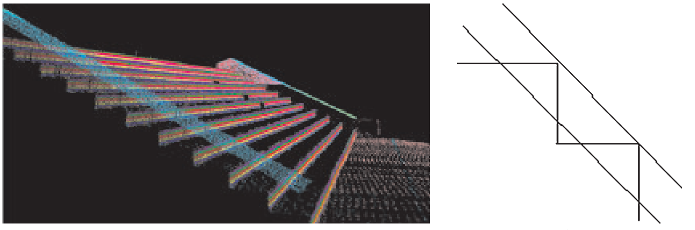


FIG. 1. The original stair point clouds.



(a) (b)

Fig. 2. Example of spurious planes obtained by the original RANSAC algorithm: (a) spurious point cloud results for plane surfaces from stairs; (b) sketch of the spurious results (oblique surfaces) for segmented surfaces.

new point cloud and the second improvement is the adaptation of the algorithm, so that it detects the best roof plane instead of the best mathematical one.

In order to deal with the previous problem, an adaptation is proposed for the RANSAC algorithm called "Seq-NV-RANSAC" to check the normal vector (NV) between the existing point clouds and the hypothesised RANSAC plane, which is created by three random points, under an intuitive threshold value.

There are many motivations for the Seq-NV-RANSAC approach:

(a) Avoiding spurious surfaces from RANSAC for parallel-gradual planar surfaces such as stairs.
(b) Creating a new approach that can deal directly with 3D point clouds from TLS.
(c) Segmenting and extracting the maximum different planar surfaces correctly, with best fit to reality, for complex objects from massive unstructured 3D point clouds in the presence of noisy data.
(d) Increase automation and reliability of segmentation results.

Methodology

In the ideal case, if the surface is planar, every neighbouring group of points must lead to the same normal vector of that original surface. Also the perpendicular distance between that point, which found some neighbours, and its plane must be equal to zero. On the other hand, in practical cases, the massive unstructured 3D point clouds could be infected by many factors, such as colour, roughness of different surfaces, the TLS instrument resolution and the registration step (Boulaassal et al., 2007). These factors affect the final results, causing the 3D point cloud even for a planar surface to appear not to be flat (that is, to have non-zero thickness). This problem can be overcome by choosing a (Tol) threshold value carefully in RANSAC based on the redundancy of acquired point clouds.

In this paper, a new automatic approach is proposed for the segmentation of planar surfaces based on the combination of the RANSAC algorithm and NV for each point and using the clustering features method to deal with massive unstructured point clouds in the presence of random noisy points (shown in Fig. 3). Firstly, the neighbours are obtained for every point as a group; secondly, NV is added for every point; thirdly, clustering point clouds based on NV divide the huge number of point clouds into small parts (parallel surfaces); and fourthly, planar surfaces are segmented based on Seq-NV-RANSAC. The approach is based on two logical assumptions:

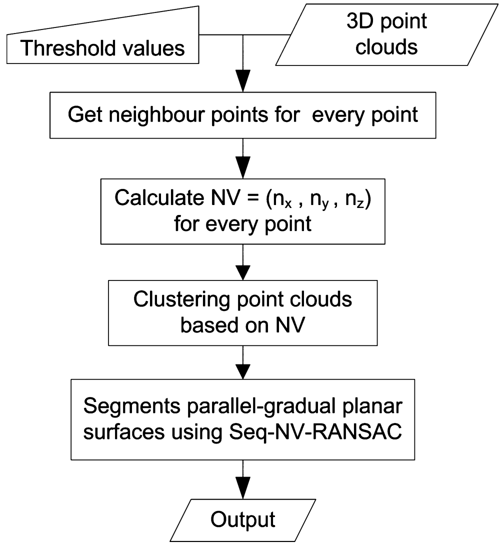


FIG. 3. Flowchart for general steps.

(1) Unlike the surface-growing method assumption that there is a part in the data-set where all points within some distance belong to the same surface (Vosselman et al., 2004), the present assumption is that most of the small parts in the data-set belong to the same surface, even when noisy points exist.
(2) Inside every neighbourhood group, most of the points must belong to the real surface. Thus the noisy points should be a small number as a ratio of the total number of points belonging to the same neighbourhood group.

Only the 3D point cloud data is obtained from the TLS instrument for every point; after the registration step is complete $P_i = (X, Y, Z)$.

The Steps

(1) Neighbour Groups and Fitting. Many methods can be used such as "k nearest neighbours" (KNN) as mentioned earlier, fixed distance neighbours (FDN) or the creation of a triangulated irregular network (TIN). In the present approach, the neighbours are acquired for every point based on the FDN method, which uses a given fixed area of interest (AOI), and the metric distance used is the Euclidean distance $E_i \in \{E_i^1, E_i^2, E_i^3, \ldots, E_i^n\}$. The intuitive threshold value E_{th} for the Euclidean distance can be easily found by the user according to the thickness and minimum point density for the acquired point clouds. The object of this step is to divide the point clouds into small neighbouring groups: $G_i = (P_i^1, P_i^2, P_i^3, \ldots, P_i^n)$; $G_i \in \{G_i^1, G_i^2, G_i^3, \ldots, G_i^n\}$. Then commonly fitting software based on the least squares method is used to calculate the plane parameters of every group $PL = (a, b, c, d) = (n_x, n_y, n_z, d)$; $PL \in \{PL_i^1, PL_i^2, PL_i^3, \ldots, PL_i^n\}$. The NV $= (n_x, n_y, n_z)$ can then be added to every original point op in every neighbouring group, and the perpendicular distance PD between op and its surface PL is calculated by

$$PD = \frac{\left|(n_x \times X) + (n_y \times Y) + (n_z \times Z) + d\right|}{\sqrt{n_x^2 + n_y^2 + n_z^2}}. \tag{2}$$

Finally, $P_i = (X, Y, Z, n_x, n_y, n_z, PD);\ P_i \in \{P_1, P_2, P_3, \ldots, P_n\}$.

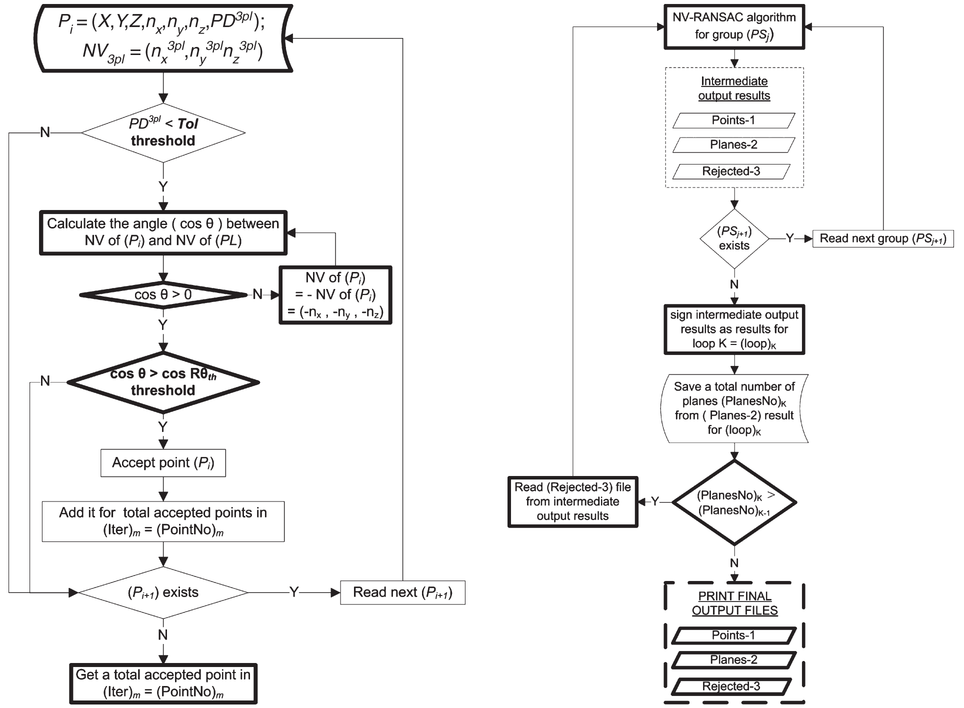
(2) Segmentation Based on Cluster Features. In this step, all points are first sorted according to PD values. Then using equation (3) the NV of each point is compared with the NV of the point with the minimum PD value under the threshold value θ_{th}. By carefully choosing θ_{th}, all points thereafter will be clustered based on NV for groups with parallel surfaces, $PS_i = (P_i^1, P_i^2, P_i^3, \ldots, P_i^n);\ PS_i \in \{PS_1, PS_2, PS_3, \ldots, PS_n\}$. Although every group could include some noisy points, this is not a problem since Seq-NV-RANSAC, in the next step, can effectively deal with noisy data from the original RANSAC algorithm. Also one of the objectives of this step is pre-processing for point clouds before applying Seq-NV-RANSAC; therefore, that step will lead to dividing the huge numbers of point clouds into suitable numbers of significant groups. Consequently, a reduced (MaxIterNo) threshold is needed for every group.

$$\mathrm{NV}_1 \times \mathrm{NV}_2 = (n_{X_1} \times n_{X_2}) + (n_{Y_1} \times n_{Y_2}) + (n_{Z_1} \times n_{Z_2}) = \cos\theta. \tag{3}$$

(3) Seq-NV-RANSAC. As mentioned in the previous brief explanation of the original RANSAC algorithm, this depends on three steps under three threshold values. In Seq-NV-RANSAC, the first aim is to avoid the spurious surfaces in the original RANSAC results for parallel-gradual planar surfaces such as stairs (shown in Fig. 2). Therefore, a new check is added to the original RANSAC; the check is based on comparing the normal vector for every point NV = (n_x, n_y, n_z) and the normal vector for the three-random-point surface obtained by RANSAC, in each iteration $\mathrm{NV}_{3pl} = (n_x^{3pl}, n_y^{3pl}, n_z^{3pl})$, under threshold value $R\theta_{th}$ using equation (3). Based on $R\theta_{th}$, Seq-NV-RANSAC can decide automatically if that point will be added to this surface's iteration or not, and by employing this check there is no way that (MaxPointNo) can be obtained from spurious surfaces. It must be noted that the NV_{3pl} direction, which is obtained by RANSAC, is based on the sequence of choosing the three points; therefore, the check also considers the opposite direction for NV. If more than one iteration has the maximum number of points (MaxPointNo), the decision on which plane to accept is then based on the minimum summation of perpendicular distances (MinSumDis) in the following equation between that plane and all its accepted points:

$$SumDis = \frac{\Sigma(PD)^2}{(PointNo)_i}. \tag{4}$$

Also for a group that has more than one planar surface, usually parallel surfaces, Seq-NV-RANSAC can successfully extract all surfaces from every group, even in the presence of noisy points, by applying all previous steps in sequence and automatically. The sequence loop will stop if no more planar surfaces can be extracted from points rejected after every loop under the existing threshold values. Then the final results for point clouds involved in each planar surface will be displayed separately in different colours. On the one hand, Seq-NV-RANSAC works in sequence and automatically. On the other hand, it has another advantage: the user can easily change one or more threshold values to extract other planes from rejected points. Fig. 4 shows the flowcharts for the main steps in the Seq-NV-RANSAC approach.



(a) (b)

Fig. 4. Flowcharts for the main steps in the "Seq-NV-RANSAC" approach: (a) flowchart for checking step for every point under NV and Tol thresholds; (b) flowchart for the sequence step.

Experimental Results and Analysis

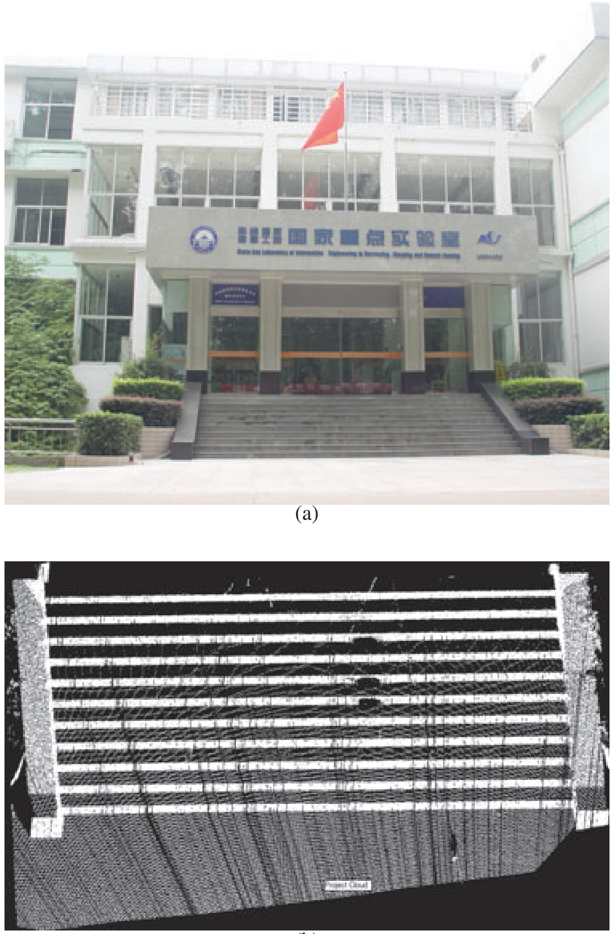
Data Description

The front entrance steps and doorposts of the State Key Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing (LIESMARS) located in Wuhan University, Wuhan, China were chosen for the study as shown in Fig. 5. [These steps are referred to as "stairs" throughout the text in order to avoid any risk of confusion with processing steps.]

A Trimble GS200 TLS (shown in Fig. 6) consists of the tripod-mounted instrument, power supply unit, transportation box and portable computer—a laptop—supported by Point Scape software for data capture. The instrument (GS200 3D) can be controlled by this software. Table I shows the main parameters of the Trimble GS200 3D laser scanner.

Results of Extraction of Surfaces using Seq-NV-RANSAC

Case Study 1: Parallel-Gradual Planar Surfaces. Once all the planar surfaces such as the stairs are extracted by Seq-NV-RANSAC, they are displayed separately with different colours as shown in Fig. 7.



(a)

(b)

FIG. 5. Full façade of LIESMARS, the sample object used in the study: (a) photograph of LIESMARS steps; (b) point clouds from LIESMARS steps (310 972 points).

FIG. 6. Trimble GS200 TLS.

TABLE I. Main parameters of Trimble GS200 3D laser scanner and typical accuracy values over varying range.

		Standard deviation	
		Range (m)	Typical value (mm)
Addressability	700 m	5	1·4
Over scan range	2 to 350 m	50	1·4
Standard range	2 to 200 m	100	2·5
Scanning speed	5000 points/s	150	3·6
Minimum resolution	3 mm@100 m	200	6·5
Horizontal field of view	360°		
Vertical field of view	−22° to +38°		

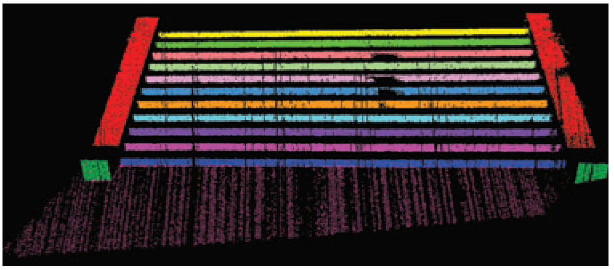


FIG. 7. Parallel planar surfaces extracted using Seq-NV-RANSAC shown with different colours.

All these results were created in sequence and automatically. Secondly, by comparing the results of extracted surfaces using Seq-NV-RANSAC shown in Fig. 7 and the original point clouds of the stairs shown in Fig. 5(b), it can be seen that all the parallel-gradual planar surfaces have been extracted successfully and no spurious surfaces occur in the stairs. Thirdly, only two surfaces, shown in Fig. 7, have the same colour (red), an under-segmentation case, meaning that the two surfaces have the same NV and are at the same level. Fourthly, some holes occur in the extracted surfaces, which are due to the original data; this can be discovered easily by comparing Fig. 7 and Fig. 5(b). Also by comparing the results of the surfaces extracted using Seq-NV-RANSAC shown in Fig. 7 and using the original RANSAC algorithm as shown in Fig. 8, the effect of the modification of the original RANSAC algorithm can be seen clearly, as all planar surfaces have been extracted successfully and without any spurious surfaces in the stairs, which are a clear example of parallel-gradual planar surfaces. According to previous comparisons between the results obtained by Seq-NV-RANSAC and the results

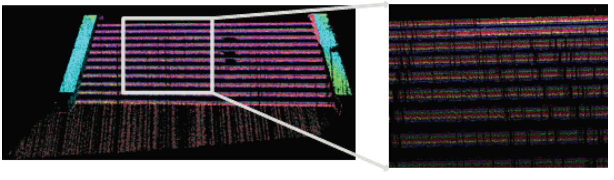


FIG. 8. The spurious plane (oblique surfaces) result shown in different colours using the original RANSAC.

obtained by the original RANSAC, the approach is working well since the result is an improvement over what could have been expected previously.

Case Study 2: Complex Building Façade. According to the final results from Case Study 1, the proposed approach has successfully achieved many of the stated objectives in this paper, since it can extract all parallel-gradual planar surfaces directly from point clouds and does not produce spurious surfaces. On the other hand, TLS instruments are designed especially for the acquisition of large quantities of data (up to some millions of points per task) with high speed. Usually large quantities of massive 3D unstructured point clouds should be obtained to cover all features for a complex façade object, which could include many planar surfaces at many different levels, such as floors, and have different NV directions such as the ground, walls with different tolerance depths, square columns, oblique surfaces with different slopes and orientations, parallel-gradual planar surfaces (stairs), windows and so on.

In order to evaluate the performance and general advantages and disadvantages of the present approach, a second case study was carried out (Case Study 2). While in Case Study 1, the number of points was 310 972, in Case Study 2 the number of points was 2 663 333 using the full point clouds of the LIESMARS façade as shown in Fig. 9 as a clear example of massive point clouds obtained for a complex façade.

After applying Seq-NV-RANSAC on the data of Case Study 2, 82 groups of planar surfaces were extracted successfully and were displayed separately with different colours as shown in Fig. 10.

On the one hand, all main planar surfaces for the complex façade, which has many different levels and many different orientations and includes parallel-gradual planar surfaces, are successfully segmented to groups in sequence and automatically using Seq-NV-RANSAC without any spurious results. On the other hand, after an analysis of the result some of these groups were found to have cases of bad segmentation (under-segmentation and over-segmentation) as expected before.

Fig. 11 shows an example of an under-segmentation case, using the same colour for one group. For example, the yellow colour shows those point clouds grouped as one group.

FIG. 9. Full point clouds of LIESMARS façade, as Case Study 2 (2 663 333 points).

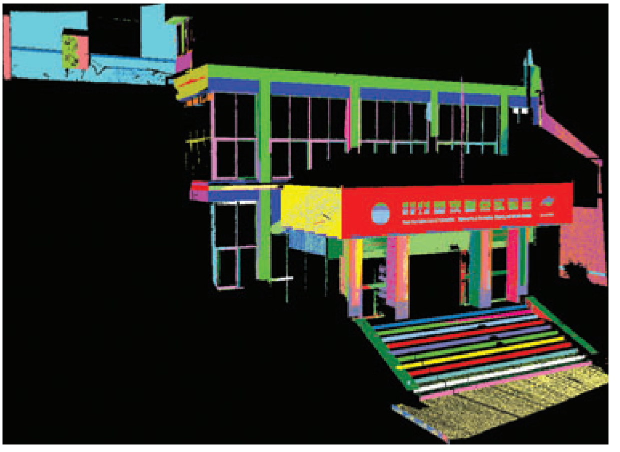


FIG. 10. Eighty-two groups of planar surfaces of LIESMARS façade extracted by Seq-NV-RANSAC from full point clouds.

FIG. 11. Examples of groups having under-segmentation, shown by different colours.

However, in reality, that one group includes many different beams (planar surfaces). It should be noted that the under-segmentation case in one group is due to these surfaces having the same NV and being at the same level (here the same depth).

Fig. 12 shows an example of an over-segmentation case, using one colour for each group. For example, the red and blue colours are expressing those point clouds that are grouped as two

FIG. 12. Examples of over-segmentation case for surfaces shown by different colours.

different groups, but in reality, those two groups belong to only one planar surface. Unlike the under-segmentation case for which there is a clear reason, over-segmentation cases can arise due to many different reasons, such as the influence of noisy points in the calculation of the initial NV for these points that leads to a big difference between a calculated NV of that point and the $R\theta_{th}$ threshold value. The choice of the (Tol) threshold value can lead to the same results, if not chosen carefully.

CONCLUSION AND FUTURE WORK

This paper presents a new approach, known as Seq-NV-RANSAC, for automatically extracting planar surfaces directly from point clouds, avoiding the spurious surfaces that can be created by the original RANSAC algorithm for parallel-gradual planar surfaces. Seq-NV-RANSAC uses the normal vectors (NV) of points as a new additional check with the original RANSAC algorithm. The normal vector check is between each point and the hypothetical RANSAC plane, which is created based on three random points, under intuitive threshold values. This process is repeated sequentially (Seq) and automatically until no planar surfaces can be extracted from the remaining points. Also the Seq-NV-RANSAC approach divides the data into small parts. That process will result in the avoidance of the spurious surfaces obtained by RANSAC; efficient computation since RANSAC will deal every time with a suitable number of points; quality improvement in the computed attributes; and an increase in the degree of automation of surface extraction. Consequently, this leads to the extracted surfaces better fitting reality. On the other hand, bad-segmentation problems can arise in some groups when encountering special cases of planar surfaces from large numbers of point clouds for a complex façade, such as two or more planar surfaces that have the same level and the same NV direction. This will lead to an under-segmentation case. Also over-segmentation can arise due to many different reasons, such as the influence of noisy points in the calculation of the initial NV for these points. However, the tools have already been devised to solve these problems in future work.

Finally, the results from Seq-NV-RANSAC have potential since they are better than previously expected and have achieved the main stated objectives of this paper. Also they encourage the automatic creation of 3D models directly from 3D point clouds, since segmentation is the essential step in the 3D modelling processes.

Future work will focus on solving the bad-segmentation problems, the extraction of surface edges and the determination of threshold parameters adaptively.

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Résumé

L'extraction d'objets dans de grands nuages de points non structurés et présentant des densités locales variables, notamment en présence de points aléatoirement bruités, n'est pas une tâche simple même si l'objet recherché est une surface plane. La segmentation est l'étape la plus importante du processus d'extraction d'objets. En pratique, la plupart des méthodes de segmentation s'appuient sur une information géométrique pour segmenter le nuage de points 3D. Les objets recherchés incluent généralement les positions de chaque point (X, Y, Z), des directions normales à la surface estimées localement et les résidus des surfaces qui optimisent l'ajustement; cependant, ces objets peuvent être affectés par des points bruités ce qui peut directement affecter le résultat de la segmentation. C'est pourquoi de grands nuages de points non structurés et bruités conduisent aussi à une mauvaise segmentation (sursegmentation, sous-segmentation ou impossibilité de segmenter). Bien que l'algorithme RANSAC (Random Sample Consensus) soit efficace en présence de bruit ou de points aberrants, il présente deux inconvénients significatifs, à savoir, d'une part, son efficacité, et d'autre part, le fait que le plan détecté par RANSAC ne coïncide pas forcément avec la surface de l'objet recherché. Ainsi, des surfaces parasites peuvent apparaître, notamment dans le cas de séries de surfaces planes comme des escaliers. L'idée innovante proposée dans cet article est une modification de l'algorithme RANSAC appelée Seq-NV-RANSAC, qui modifie le vecteur normal entre les nuages de points existants et le plan supposé par RANSAC, lequel est créé par trois points au hasard, au-dessous d'une valeur seuil intuitive. Après l'extraction du premier plan, le processus est répété séquentiellement et automatiquement jusqu'à ce que plus aucune surface plane ne puisse être extraite des points restant au-dessous du seuil. Cela empêche l'extraction de surfaces *parasites, améliore la qualité des attributs calculés et accroît le degré d'automatisation de l'extraction de surfaces. On obtient un résultat optimal pour des surfaces existantes.*

Zusammenfassung

Die Erfassung von Objektmerkmalen großer, unstrukturierten Punktwolken mit unterschiedlich lokalen Dichten und bei verrauschten Punkten ist keine einfache Aufgabe, auch wenn nur eine ebene Oberfläche extrahiert werden soll. Segmentierung ist der wichtigste Schritt bei der Merkmalsextraktion. In der Praxis nutzen die meisten Segmentierungsansätze geometrische Information, um die 3D Punktwolke zu segmentieren. Die Merkmale umfassen üblicherweise die Lage jeden Punktes (X, Y und Z), die lokal bestimmte Oberflächennormale und Verbesserungen für angepasste Oberflächen: allerdings können diese Merkmale durch verrauschte Punkte beeinflusst werden, und damit auch die Ergebnisse der nachfolgenden Segmentierung. Daher können stark unstrukturierte und verrauschte Punktwolken zu schlechten Segmentierungen führen (Übersegmentierung, Untersegmentierung oder sogar keiner Segmentierung). Während der RANSAC (Random Sample Consensus) Algorithmus effektiv bei Rauschen und groben Fehlern arbeitet, hat er doch zwei signifikante Nachteile: seine Effizienz und die Ebene, die mit RANSAC detektiert wurde muss nicht unbedingt zu der gleichen Oberfläche gehören, d.h. unechte Oberflächen können generiert werden. Dies ist vor allem im Fall von stufenweise ebenen Oberflächen wie bei Treppen gegeben. Die Innovation dieses Beitrages liegt in der Modifizierung des RANSAC Algorithmus, dem sogenannten Seq-NV-RANSAC. Dieser Algorithmus prüft, mit Hilfe eines intuitiven Schwellwertes, den Normalenvektor (NV) zwischen den existierenden Punktwolken und der Hypothese der RANSAC Ebene, die durch 3 zufällige Punkte festgelegt wird. Nach der Extraktion der ersten Ebene, wird dieser Prozess sequentiell (Seq) automatisch wiederholt, bis keine weiteren ebenen Oberflächen aus den verbliebenen Punkten bei den gegebene Schwellwert extrahiert werden können. Dies verhindert die Extraktion von virtuellen Oberflächen, ergibt eine Qualitätsverbesserung der berechneten Attribute und erhöht den Grad der Automation bei der Oberflächenextraktion. Damit wird die beste Übereinstimmung für die vorliegenden Oberflächen erreicht.

Resumen

La extracción de objetos a partir de nubes no estructuradas de puntos con diferentes densidades locales, especialmente en presencia de puntos ruidosos aleatorios, no es una tarea trivial incluso si el objeto es una superficie plana. La segmentación es el paso más importante en el proceso de extracción de objetos. En la práctica, la mayor parte de los procedimientos de segmentación utilizan información geométrica para fragmentar la nube de puntos tridimensional. Habitualmente los objetos incluyen información de la posición de cada punto (X, Y y Z), las normales a la superficie estimadas localmente y los residuos de las superficies de mejor ajuste. Sin embargo estos objetos podrían verse influenciados por puntos ruidosos y, consecuentemente, afectar directamente a los resultados de la segmentación. Por lo tanto, las nubes de puntos ruidosos no estructuradas y masivas también dan lugar a una segmentación inadecuada (sobresegmentación, infrasegmentación, o falta de

segmentación). Aunque el algoritmo RANSAC (Random Sample Consensus) es eficaz en presencia de ruido y valores extremos, tiene dos desventajas: su baja eficiencia y el hecho de que el plano detectado por el algoritmo RANSAC no tiene por qué pertenecer necesariamente a la misma superficie del objeto. Esto quiere decir que pueden aparecer superficies espurias, especialmente en el caso de superficies planas, graduales y paralelas, como en el caso de escaleras. La idea novedosa propuesta en este artículo es una modificación del algoritmo RANSAC, denominada Seq-NV-RANSAC, que verifica si el vector normal entre las nubes de puntos disponibles y el plano determinado por RANSAC, que se construye a partir de tres puntos aleatorios, está por debajo de un umbral intuitivo. Tras extraer el primer plano, el proceso se repite secuencial (Seq) y automáticamente hasta que no se pueden extraer más superficies planas a partir de puntos restantes por debajo de los umbrales establecidos. Esto evita la extracción de superficies espurias, mejora la calidad de los atributos calculados e incrementa el nivel de automatización de la extracción de superficies. De este modo se obtiene el mejor ajuste para las superficies existentes.

