3D SEGMENTATION OF UNSTRUCTURED POINT CLOUDS FOR BUILDING MODELLING

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ABSTRACT:

The determination of building models from unstructured three-dimensional point cloud data is often based on the piecewise intersection of planar faces. In general, the faces are determined automatically by a segmentation approach. To reduce the complexity of the problem and to increase the performance of the implementation, often a resampled (i.e. interpolated) grid representation is used instead of the original points. Such a data structure may be sufficient for low point densities, where steep surfaces (e.g. walls, steep roofs, etc.) are not well represented by the given data. However, in high resolution datasets with twenty or more points per square-meter acquired by airborne platforms, vertical faces become discernible making three-dimensional data processing adequate. In this article we present a three-dimensional point segmentation algorithm which is initialized by clustering in parameter space. To reduce the time complexity of this clustering, it is implemented sequentially resulting in a computation time which is dependent of the number of segments and almost independent of the number of points given. The method is tested against various datasets determined by image matching and laser scanning. The advantages of the three-dimensional approach against the restrictions introduced by 2.5D approaches are discussed.

1. INTRODUCTION

Numerous disciplines are dealing with the problem of geometric surface modelling from unstructured point clouds. These are, for example, computer vision, reverse engineering, or photogrammetry. In this article, we are studying segmentation for the purpose of building modelling from large, three-dimensional point clouds. Our ambition is the definition of a highly robust approach with respect to the method used for point sampling (i.e. image matching or laser scanning), measurement noise, scaling issues, and coordinate system definition implying three-dimensional applicability. Additionally, a low time complexity is required in order to process huge datasets.

The typical workflow from data (point) acquisition towards the final, geometrical surface model (e.g. triangulation or constructive solid geometry) consists of the following steps: Calibration (i.e. elimination of systematic effects), registration (in photogrammetric context often referred to as orientation), minimization of the influence of measurement noise (referred to as filtering or smoothing), and finally, surface modelling. Systematic errors should be eliminated by instrument calibration prior to the measurement (i.e. by the manufacturer) or a posteriori during data processing (if the behaviour of the systematic errors is known) or by self-calibration of the system (e.g. Lichti & Franke (2005) for terrestrial and Kager (2004) for airborne laser scanners). In this paper, we do not discuss calibration and registration, while the other two steps, namely random error (i.e. noise) elimination and modelling are considered. The starting point is therefore a set of points in three-dimensional Cartesian space without systematic but with random errors.

By means of segmentation, points with similar attributes are aggregated, thus, introducing an abstraction layer. This simplifies subsequent decision making and data analysis, as compound objects defined by multiple points are represented by segments. Higher level objects are easier to deal with compared to original point cloud handling, simplifying many applications such as object detection, recognition or reconstruction. Additionally, the data volume decreases significantly when handling the segments' parameters only instead of the original point cloud. Thus, the computation time of subsequently applied algorithms may decrease.

In general, the workflow for building reconstruction from point cloud data can be separated in three steps: *Building detection*, *determination of planar faces* representing individual roof planes and finally *model generation*. Point cloud segmentation as described within this article provides planar faces which can be used for the determination of building models thus, supporting the latter two steps. The first step, namely building detection, is not discussed in the following, as we assume to initiate building modelling from given, two-dimensional boundary polygons for each building. Numerous approaches for the automated determination of building boundaries can be found in literature. For example, Rottensteiner et al. (2004) and Haala & Brenner (1999) describe methods integrating laser scanning and multi-spectral image data, Maas & Vosselman (1999) introduced a triangle-mesh based approach demonstrated

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on laser scanning data and, Zebedin et al. (2006) describe a method based on matched points. Brenner (2003) gives an overview on automatic and semi-automatic systems for building reconstruction from image and laser scanner data.

Many approaches for the determination of planar faces for roof modelling from point clouds acquired from airborne platforms can be found in literature (e.g. Maas & Vosselman (1999), Lee & Schenk (2002), Filin (2004), or Vosselman & Dijkman (2001)). To reduce the complexity of the problem and to increase the performance of the implementation, often a resampled (i.e. interpolated) grid representation is used instead of the original points (e.g. Alharty & Berthel (2004), Rottensteiner et al. (2005)). Such a data structure may be sufficient for low point densities, where steep surfaces (e.g. walls, steep roofs, etc.) are not well represented by the given data. However, in high resolution datasets with twenty or more points per square-meter acquired by airborne platforms, vertical faces become discernible making three-dimensional data processing adequate.

Characteristics and acquisition of unstructured point clouds, basic characteristics of segmentation and the computation of highly robust, local regression planes are introduced in Section 2. Our segmentation algorithm is presented in Section 3, starting with a comparison to a grid-based approach our work was inspired by. In Section 4 results derived from image matching and laser scanning point clouds are presented. In Section 5, we discuss the characteristics of 2.5D and 3D segmentation and analyze the performance of our approach.

2. RELATED WORK

So far, we stated the applicability of our segmentation approach on unstructured point clouds, but without defining our understanding of the latter terminus. This is done in Section 2.1, followed by the definition of our understanding of segmentation in order to avoid misunderstandings (Section 2.2). The determination of highly robust, local regression planes for every given point is of crucial importance for our segmentation algorithm. Therefore in Section 2.3, the basic characteristics of the method used are presented.

2.1 Acquisition of Unstructured Point Clouds

We define an unstructured point cloud as a set of points, obtained from a random sampling of the object's surface in a three-dimensional way. No additional definition according to the reference frame (e.g. a reference direction) or the metric (e.g. scaling) are made. Numerous acquisition methods for the determination of such point clouds do exist. As we are studying the reconstruction of buildings in this article, we are concentrating on data acquisition methods from airborne (i.e. helicopter or airplane) and satellite borne platforms. The point determination is performed either directly through polar single point measurement (e.g. Lidar – light detection and ranging – often referred to as laser scanning or synthetic aperture radar (SAR) often performed by satellites) or indirectly (e.g. stereoscopic image matching). However, all these techniques deliver unstructured point clouds according to our definition. The segmentation results presented in this paper were derived from point clouds determined by image matching (IM) and airborne laser scanning (ALS), both acquired from airborne platforms.

2.2 Segmentation of Point Clouds

Segmentation refers to the task of partitioning a set of measurements in the 3D object space (point cloud) into smaller, coherent and connected subsets. These subsets should be 'meaningful' in the sense that they correspond to objects of interest (e.g. roofs, trees, power cables) or parts thereof (roof planes). Often, the segments are assumed to take the form of simple geometric primitives (e.g. planar patches). In this case segmentation and extraction of the primitives are typically performed simultaneously, rather than sequentially. We assume that the resulting segments $\mathbf{R}_i$ (a sub-set of points) of $\mathbf{R}$ (all N points) meet the following requirements (Hoover et al., 1996):

1. $\bigcup_{i=1}^{N} \mathbf{R}_i = \mathbf{R}$ (requires the definition of a rejection-segment)
2. $\mathbf{R}_i \bigcap \mathbf{R}_j = \{\}$, for $i \neq j \wedge 1 \leq i, j \leq N$
3. $\mathbf{R}_i$ is a connected component in the object space, for $1 \leq i \leq N$
4. $P(\mathbf{R}_i) == true$ for some coherence predicate P, $1 \leq i \leq N$
5. $P(\mathbf{R}_i \bigcup \mathbf{R}_j) ==$ false for adjacent $\mathbf{R}_i$, $\mathbf{R}_j$ with $i \neq j \wedge 1 \leq i, j \leq N$

(1)-(2) state that the resulting segmentation is a partitioning of the original point cloud, i.e., a decomposition into disjunct subsets. The connectivity requirement (3), which is straightforward in image processing (since there, connectivity is defined in terms of the 4- or 8- neighbourhood on the pixel grid), requires a definition of neighbourhood (topology) for unstructured point clouds. This could be done, for example, by considering two points as neighbours if they are connected by an edge in the Delaunay triangulation; however, obtaining the Delaunay triangulation is computationally costly (in particular, for large point clouds). Hence, we use a criterion based on the Euclidean metric: $\mathbf{R}_i$ is a connected component if the distance of any point to its nearest neighbour in the segment is below a given threshold. The coherence predicate in (4) simply states that the points must lie on (or near) the same instance of a parametric primitive (in our case, a planar patch). Finally, (5) requires that the points belonging to two adjacent segments lie on two separate planes (otherwise, the segments are merged).

2.3 Robust Local Regression Planes

It can be assumed that the normal vectors (short: normals) of local regression planes of points belonging to a segment (i.e. plane) are almost identical. According to the given task, several requirements for the plane fitting algorithm are introduced. These are the capability to handle a high noise level, robustness at sharp surface features (e.g. planes intersecting at a common edge) and mode seeking behaviour due to the uncertainty of the distribution of the measurement errors which might not be symmetric.

Commonly used methods for regression plane estimation are, for example, moving least squares (e.g. Levin, 1998) or iteratively reweighted least squares (e.g. Hoaglin et al., 1983). Unfortunately, both methods are sensitive against non-symmetric point density. Additionally, the former is not robust against noise while the latter may handle noise well, but the result can be influenced by a single lever point (breakdown point of zero percent). The Random Sampling Consensus Algorithm (RANSAC) (Fischler & Bolles, 1981) is often

referred to in literature. But RANSAC does not consider statistics, behaves slow and has an insufficient breakdown point with respect to our task. Furthermore, RANSAC uses the object space (i.e. point position) only and cannot take additional parameter (e.g. local normals) into account. Therefore, we developed a method which fulfils the stated requirements as much as possible while achieving acceptable computation time as well. It is based on the Fast Minimum Covariance Determinant (FMCD) approach, described by Rousseeuw & van Driessen (1999) for application in the field of data mining. Filin (2004) investigated a prior approach described by Rousseeuw in the field of ALS-point classification and indicated it as too slow for that application. By introducing heuristics, the performance of this approach is sufficient for the given task.

3. METHODOLOGY

Our research has been inspired by a grid-based (in the following referred to as 2.5D) approach described by Pottmann & Wallner (1999). The method's application to building modelling was first described by Peternell & Pottmann (2002). We compare this method to our algorithm which is applicable on three-dimensional point clouds and behaves independent from the coordinate system definition. By means of a sequential implementation of the clustering algorithm used, the time complexity of the three-dimensional approach behaves better than the 2.5D-implementation by Pottmann et al.

3.1 Distance Measure between Planar Faces

Hierarchical clustering in the four-dimensional feature space defined by the local regression planes of the given points (Section 2.3) requires an appropriate distance measure. A plane in three-dimensional Cartesian coordinates is defined by

$$0 = a_0 + a_1 x + a_2 y + a_3 z \qquad (1)$$

with a_1, a_2, a_3 representing the local unit normal vector of the plane and a_0, the normal distance of the plane to the origin of the coordinate system. To determine a three-dimensional measure of distance between two planes $A = (a_0, a_1, a_2, a_3)$ and $B = (b_0, b_1, b_2, b_3)$, we define the distance d over an area of interest Γ in the following way:

$$d_\Gamma(A, B)^2 = \int_\Gamma (c_0 + c_1 x + c_2 y + c_3 z)^2 \, dxdydz \qquad (2)$$

where $c_n = a_n - b_n$

The integrand of (2) represents the squared difference of the orthogonal distances from a point to the two planes A and B. Thus, the integral over all squared distances within Γ can be interpreted as a mean squared distance between these planes, if it is normalized by the volume of Γ. As we consider squared differences, greater differences become a higher weight. But this does not matter, as we aim at the determination of similar planes (i.e. with small differences). The application of this measure in 2.5D space over a planimetric, rectangular Γ (as described by Peternell & Pottmann (2002)) obviously is dependent on the definition of the reference direction (in general z). The distance measures d for two planes (A, B) enclosing an angle of one degree, intersecting within the system's origin ($a_0 = b_0 = 0$) and rotating around the y axis are shown in Figure 1 (chain dotted

line). The behaviour of a three-dimensional d (Eq. 2) with a bounding box (dashed line) and a bounding sphere (continuous line) are superimposed. While for the 2.5D case the distance measure becomes useless for inclination angles between 45° and 135° respectively 225° and 315° (the measure increases at least by a factor of two and becomes infinite in the worst case occurring if a plane is vertical), the box-based 3D measure is almost and the sphere-based measure really is constant.
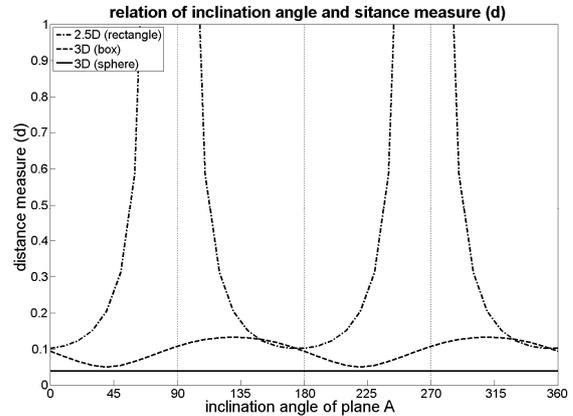
Figure 1. Relation of inclination angle against the horizontal *xy*-plane and different distance measures d demonstrated by two planes (inclined by 1°) rotated around the *y*-axis.

3.2 Implementation

A global clustering approach requires the evaluation of the distance measure d for each pair of given points. This results in a time complexity of $O(n^2)$ with n representing the number of points given. Considering datasets with millions of points, this is not feasible. Therefore, we replaced the determination of the distance matrix by a sequential evaluation of the given plane parameters. This reduces the time complexity to $O(m)$ with m representing the number of detectable planar faces.

The clustering in feature space is used to determine seed-clusters. For each seed-cluster, a region growing is performed. This is done by assigning points to the plane segment if they are within a normal distance band around the seed-cluster's plane and if the distance d between the points' normals and the seed-cluster's regression plane is smaller than a predefined threshold. If no more seed-cluster can be determined, the remaining points are assigned to the rejection class. Afterwards, a connected component analysis in object space and a merging of similar components considering feature and object space are performed.

Figure 2 shows the segmentation of a building from an unstructured point cloud. The distance measure used in feature space, the normal distance threshold in object space and the standard-deviation (σ) used to determine outliers during robust plane estimation have been set to 0.1m. Figure 2(a) and (b) show the determination of segment 1, (c) and (d) of segment 2, and (e) and (f) the final segmentation of the building including vertical walls. (a) and (c) show the points of the seed-clusters (large black dots). Points accepted in object and feature space are shown in light grey. Subsequently, a robust regression plane is fitted through these points using a 3σ threshold for outlier detection. The results of the plane fitting are shown in (b) and (d). Accepted points are shown in light grey; outliers in dark grey. The small light grey dots in (c) and (d) represent points already assigned to segment 1; black points have not been used so far.

Points accepted in object space but neglected in feature space are shown in (a) and (c) in dark grey. Algorithms taking into account object space only (e.g. RANAC) might use these points as support for the final plane determination. This may introduce problems for example along the intersection of two planes. As demonstrated by (c), numerous points along the gable of the roof were assigned to the plane defining the dormer. Without the normals' based decision criterion, these points might have been assigned to the dormer plane.

a   b

c   d

e   f
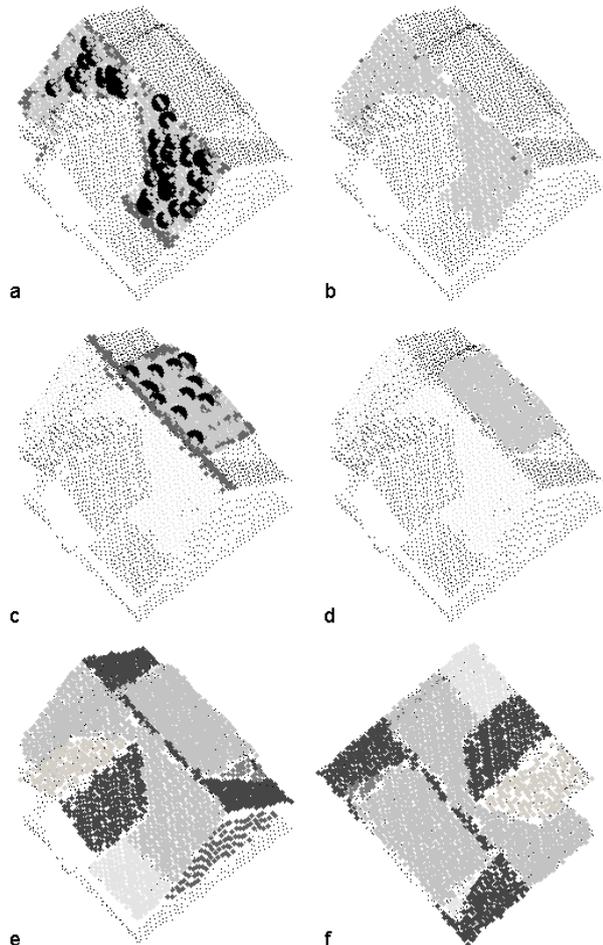
Figure 2. Segmentation of a building. (a) and (b) show the determination of segment 1; (c) and (d) of segment 2. (e) and (f) show the final segmentation including vertical walls.

4. APPLICATIONS

As mentioned in Section 2.1, digital image matching and airborne laser scanning are well suited for the determination of unstructured point clouds of a landscape. In the following, we present building models derived from segmentation results which were determined by the described segmentation algorithm. The building models were generated by piece-wise intersection of planar faces. Similar approaches can be found in literature (e.g. Maas & Vosselman (1999), Park et al. (2006)). In general, roof landscape modelling from airborne point clouds results in 2.5D descriptions of real world objects. This introduces restrictions with respect to the achievable level of detail. For example, roof overhangs can not be considered and vertical walls are defined at the eaves. Due to the high point density of the given dataset (~20 points per square-meter), numerous points at vertical façades have been determined

(confer Figure 2), allowing to reconstruct the real position of the vertical walls (i.e. a planar representation of façades). Subsequently, roof overhangs can be modelled properly. The high point density was enabled by a helicopter borne platform at a low flight level. The large opening angle (±22.5°) of the scanner used (Riegl LMS-Z560i) (http://www.riegl.com) and multiple overlaps allowed the acquisition of the façade points.
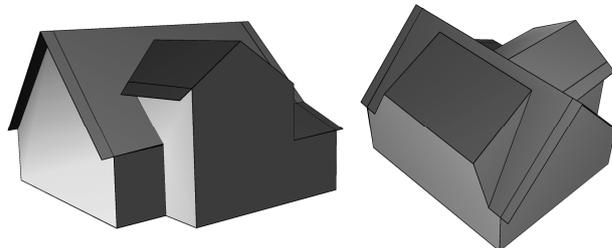
Figure 3. Detailed model of a building determined by piece-wise intersection of planar faces based on the segmentation shown in Figure 2.

The second example was derived from a matched point cloud. The images have been acquired by a *Vexcel UltracamD* (http://www.vexcel.com). The matching was done using the software *Match-T* from *Inpho* (http://www.inpho.de). Compared to the ALS data noise level is higher. Thus, a larger neighbourhood (i.e. more points) was used to determine the local regression planes. Hence, the minimum size of discernible faces is larger compared to the processed ALS data. Nevertheless, the segmentation and the building model derived from the matching points appear plausible (Figure 4), demonstrating the robustness of the segmentation with respect to the data acquisition method used.
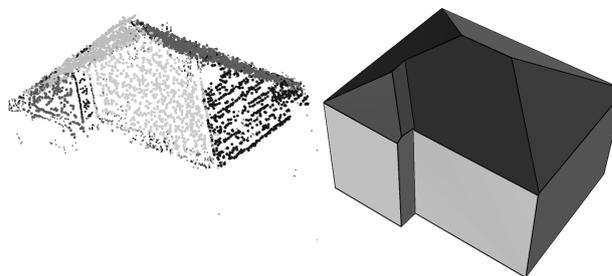
Figure 4. Segmentation of a matched point cloud (left) and building model (right).

5. DISCUSSION

Cadastral information is normally based on the polygonal boundaries of buildings at the terrain level. In most cases, this 2.5D polygon differs from the normal projection of the eaves on the terrain as most roofs have an overhang. 2.5D building modelling approaches cannot cope with this, making the resulting models unsuitable for gathering or updating cadastral information. However, we demonstrated that the determination of the real position of vertical walls from high density ALS data is possible (Figure 2) using a three-dimensional segmentation approach. The integration of this information in the modelling process is shown in Figure 3. In this example, it was not possible to determine the real position of all walls. In Figure 5 points on vertical walls (white lines) acquired by airborne laser scanning are shown. Obviously, the distribution of these points depends on the flight configuration. Thus, it can be influenced by an adequate flight planning.

Figure 5. Points on vertical planes (façades).

To demonstrate the effect of data resampling (i.e. grid interpolation) on the segmentation of the point cloud, a regular grid (25 cm) was derived from the dataset shown in Figure 2 by means of linear prediction ($\sigma = 5$ cm). Figure 6 shows the segmentation of this grid. Several erroneous segments were found along the intersection lines of touching segments.
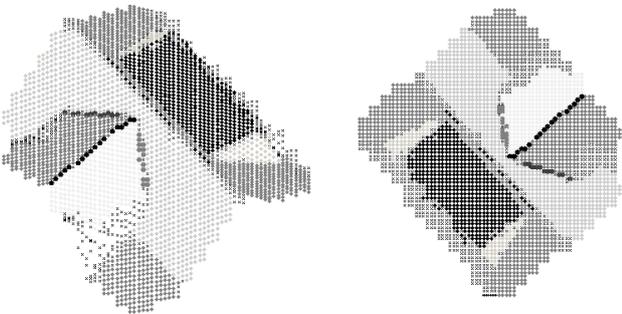
Figure 6. Segmentation of a 25 cm grid derived from the original point cloud. The smoothing of the grid interpolation causes erroneous segments.

Figure 7 shows the differences of the exposure and slope determined from the parameters of the planar faces derived from the original and the resampled point cloud (confer Figure 2 and 6). The differences of the planes 1 to 6 are not significant and seem to be randomly distributed, while the planes 7 and 8 show significant differences. These are the smallest faces (i.e. the are supported by the least number of points) representing the triangular faces of the huge dormer. As no reference data is available, we are not able to decide which parameters are the correct ones.
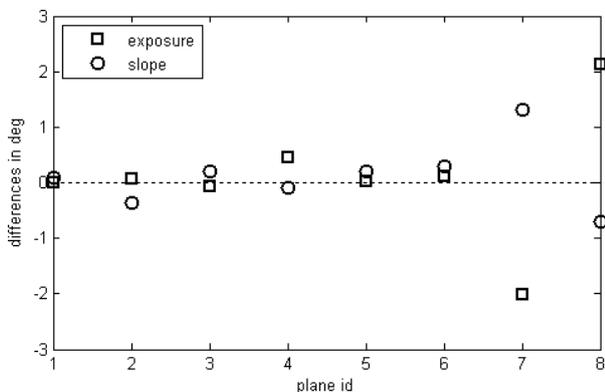
Figure 7. Differences of exposure and slope determined from the parameters of the planes derived from the original and the resampled point cloud.

The segmentation of buildings as presented in this paper including connected components analysis takes about a second. To investigate the time performance behaviour of the segmentation in more detail (not considering the connected components analysis), synthetically generated datasets were used. These datasets are three orthogonal prisms with rotation axes that are collinear with the axes of the coordinate system and thus, intersecting at the origin of the coordinate system. Every prism consists of n rectangular planes defined by m points. A normally distributed random noise was added in normal direction to each plane. Figure 8 shows such an object defined by 12 planar faces per prism. The original object is shown left while the segmentation result is shown right.
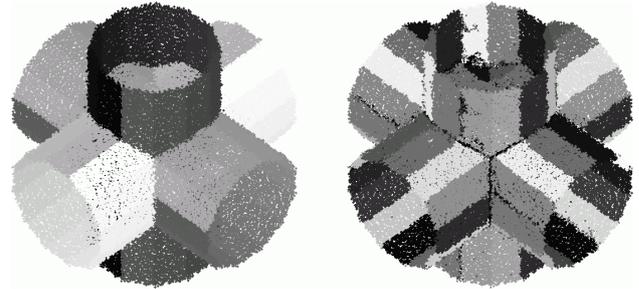
Figure 8. A synthetically generated dataset consisting of 36 planar faces, aligned in numerous directions with respect to the coordinate system. The left figure shows the original planar faces. The segmentation is shown right.

Increasing the number of object points defining similar objects (i.e. equal extension, 12 faces per prism, different point spacing (n=constant; m=increased)) by a factor of 150 (720 to 114,156 points) increases the computation time of the segmentation by a factor of 4 only (1.3 to 6.1 sec.). The computation time for the segmentation is shown as solid line in Figure 9 (left). Figure 9 (right) shows the relation of an increasing number of faces while the number of points is almost constant (n=increased; $m \cdot n$=30,000). In this example, the number of faces is increased by a factor of 6 (9 to 54 faces) while the computation time increases by a factor of 3 (1.1 to 3.2 sec.). The time for normal estimation is shown as dotted line in both diagrams. It scales almost linear by the number of given points.
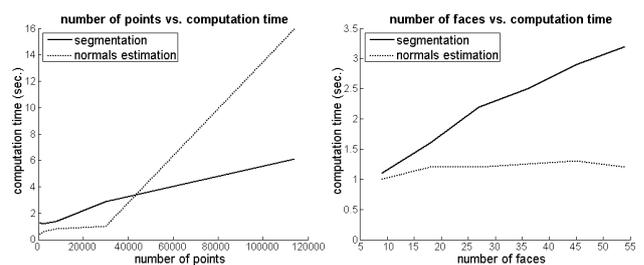
Figure 9. Influence of the number of points (left) and the number of faces (right) on the computation time.

6. CONCLUSIONS

Many building modelling approaches based on unstructured point clouds acquired from airborne platforms (i.e. airplane or helicopter borne) generate 2.5D representations of the real world objects for different reasons. On the one hand, most available datasets do not provide enough information to model vertical structures (i.e. façades) or even roof overhangs in a proper manner. On the other hand, approaches based on gridded

data structures are commonly used as they are likely to increase the performance.

However, currently available data acquisitions systems allow for the determination of numerous structures on vertical walls of buildings and similar objects by means of appropriate flight conditions (low flight level, great opening angle, multiple overlaps, …). Furthermore, the restrictions of 2.5D can be overcome by introducing real three-dimensional point cloud segmentation and subsequent modelling approaches. We presented such a segmentation approach in detail which was originally inspired by a 2.5D approach. By means of a smart implementation of the algorithm, the time complexity of the problem was reduced, thus resulting in lower computation time with respect to the original, 2.5D approach.

The segmentation algorithm was tested on point clouds acquired by laser scanning and image matching. The results, which appear reliable, were used for subsequent determination of building models. This was done using an approach based on piece-wise intersection of touching plane segments.

The presented comparison of 2.5D and 3D data processing demonstrated that the determined plane parameter may differ significantly, especially for small faces with less support points. These results should be analyzed further using reliable ground truth measurements.

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