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Extraction of 3D planar Primitives from Raw Airborne Laser Data: a Normal Driven RANSAC Approach

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Abstract

Airborne laser data are nowadays well-known to provide regular and accurate altimetric data. Building reconstruction strategies from traditional stereo images may highly be enhanced using such data together with. The aim of this paper is to propose an efficient algorithm for extracting 3D planar primitives from a laser survey over urban areas. It is based on a normal driven random sample consensus (ND-RANSAC) which consists of randomly selecting sets of three points within laser points sharing the same orientation of normal vectors. A robust plane is then estimated with laser points that are likely to belong to the real roof facet. The number of draws is managed automatically with a statistical analysis of the distribution of normal vectors within an approximation of the Gaussian sphere of the scene. Promising results are presented with laser data acquired over the city of Amiens, France.

1 Introduction

For the last past years, laser altimetry has become an accurate technique to describe topography from an airborne platform. Initially, it provides a set of laser strips (3D point clouds) acquired by means of laser distance measurements, combined with an integrated GPS/INertial System [6]. The entire post-processing of laser data has nowadays reached a high level of automation. It consists of three main steps:

i. Adjusting strips with regard to each other to provide a global coherent point cloud over a survey

ii. Filtering the point cloud into ground/non-ground points

iii. Analyzing and generating models of specific landscapes.

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We consider that step i and ii have already been processed with standard algorithm. We would like to focus this study on the third item, more precisely on the building reconstruction problem. Accurate 3D building retrieval is the main objective of the forthcoming 3D urban cartography. The aim of this study is to explore the potentialities of using solely 3D laser data to detect 3D planar hypothesis of roof facets over a set of *connected* buildings.

Many authors have tackled the problem so far. Haala and Brenner [2] extract planar roof primitives from dense altimetry data by planar segmentation algorithms (region growing onto normals), using additional ground plane information for gaining knowledge on topological relationships between roof planes. Maas and Vosselman [7] proposed a first solution involving invariant moments of point clouds. A second approach, also studied by Hofmann [4], consists of detecting planar faces in a triangulated point set, investigating the parameter space of planes (dual space of 3D points). Plane directions are extracted through a 3D cluster analysis on the Gaussian sphere. An obvious disadvantage of this technique is that parallel planar faces cannot be separated directly on the Gaussian sphere. Pottman [9] proposes to use a special distance to measure the proximity of planes and then to enhance the 3D clustering process. An other approach [11] is based on the well-known 3D Hough transform to detect planar faces from the irregularly distributed point clouds.

This paper proposes an alternative solution to detect roof facets of buildings based on a Normal Driven RANSAC (RANdom SAmple Consensus) related approach. Having presented the RANSAC algorithm, we will describe our modified approach before showing some results and concluding.

2 Background

The RANSAC algorithm introduced by Fischler and Bolles [1] with applications to the context of roof facet detection would be formulated as follow (cf. algorithm 1): randomly select a set of N plans

(3 points m) within a point cloud $\mathcal{S}$ and keep memory of the number of points (supports) which distance from the associated planes are less than a critical distance (d). A least square estimation of the final plane ($\mathcal{P}_{final}$) is performed with the set of supports ($\mathcal{M}_{final}$) belonging to the plane with the highest score. The set $\mathcal{M}_{final}$ is then extracted from the initial point cloud $\mathcal{S}$. The algorithm runs until $card(\mathcal{S}) < 3$.

Algorithm 1 Basic RANSAC for detecting roof facets

repeat
  while $n \leq N$ **do**
    Randomly select a plan $\mathcal{P}$ (3 points)
    $\mathcal{M} = \{m \in \mathcal{S} / \|m - \mathcal{P}(m)\| \leq d\}$
    $\mathcal{M}_{card(\mathcal{M})} \leftarrow \mathcal{M}$
    $n = n + 1$
  end while
  $\mathcal{M}_{final} = \arg\max_{n \in \mathbb{N}} \mathcal{M}_n$
  $\mathcal{P}_{final} = \arg\min_{\mathcal{P}'} \sum_{m \in \mathcal{M}_{final}} \|m - \mathcal{P}'(m)\|^2$
  $\mathcal{S} \leftarrow \mathcal{S} \backslash \mathcal{M}_{final}$
until $card(\mathcal{S}) < 3$

This approach may be extremely time consuming since we must ensure a minimum number of draws (N) so that a correct plan $\mathcal{P}$ should be instantiated. Most often it is not worthy to try all possible draws [3]. In other words, for a given probability p of drawing a correct plane $\mathcal{P}$ (that is three points without outlier), we would like to maximize the probability w that any selected point is an inlier (w^3 for 3 points). p, w and N are related to each other by the following equation :

$$(1 - p) = (1 - w^3)^N \Leftrightarrow N = \frac{log(1 - p)}{log(1 - w^3)} \quad (1)$$

N can therefore be calculated directly from the knowledge of p and w. p is generally kept constant to 0.99. The general idea of this paper is that searching for the roof facets where they really could be located should highly improve the efficiency of a blind RANSAC approach. In our context, main plane directions correspond to roof facet orientations. As a result, focusing the consensus onto regions sharing the same normal orientation will constrain the probability w to follow specific statistical rules as developed in section 3.2.2.

3 Theory

3.1 Point clustering based on surface normal estimation

There are several methods for obtaining local surface normal from range data [8]. These normals are then processed for segmenting planar surface regions of range images like the fast segmentation method of Taylor [10]. It is a split-and-merge method, where the homogeneity criterion is based on the comparison of two angles describing the normal orientation and the original range value. Merging is based on simple minimum and maximum value comparison of neighboring regions.

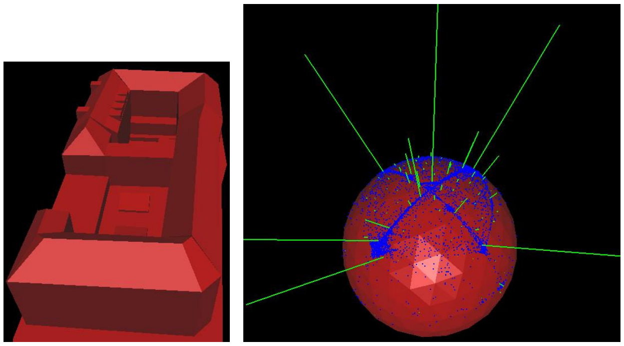
Here, we propose a planar segmentation of the laser point cloud by analyzing the Gaussian sphere (GS) of the scene. Normal vectors are calculated over a regular grid by extracting a circular neighboring of the central 3D point. A plan is then estimated using a robust regression of M-estimators' family with the norm $L_{1.2}$ [12]. The mass density of the normal vectors on the GS is described by an extended Gaussian image (EGI) [5]. First, the GS can be approximated by a tessellation of the sphere based on regular polyhedrons. Such tessellation is computed from a geodesic dome based on the icosahedron divided into f sections (f is a power of 2). The EGI can be computed locally by counting the number of surface normals that belong to each cell. The values in the cells can be thought as an histogram of the orientations.

The angular spread (related to the number of faces) depends on the error we tolerate for the coherence of the normal vectors in a cell. As a result, within a specific cell, normals $\begin{pmatrix} n_x \\ n_y \\ n_z \end{pmatrix}$ will be distributed following a certain density of probability $p(n_x, n_y, n_z)$, which will be analyzed in the next section.

Each cell with a minimum number of laser points is affected to the corresponding image of normal vectors. Regions sharing the same normal orientation are detected. They are then labeled providing a set of clusters which are ordered depending on their surface. We will see that only most represented orientations (largest areas) will be treated selecting laser points belonging to these areas.

3.2 The ND-RANSAC algorithm

The RANSAC algorithm is a general robust approach to estimate models. Instead of using as much as of the data as possible to obtain an initial solution and then attempting to eliminate the invalid data point, RANSAC uses as small data set as feasible and enlarges this set with consistent data when possible. Two parameters have to be tuned: the critical distance and the number of draws. The first one depends on the noise ratio of the data while the second one depends on the statistical distribution of points onto the Gaussian sphere.



(a) (b)

Figure 1: (a) Vector model of a synthetic building generated by manual restitution from aerial images (b) Orientation histogram collected on a geodesic dome derived from the icosahedron (there are 500 faces). This is a discrete approximation of the EGI calculated only onto non vertical planes of (a). The length of the **green** vectors attached to the center of a cell is proportional to the number of surface normals which fall within the range of directions spanned by that cell. **Blue** points are the projection of normals onto the Gaussian sphere.

3.2.1 The critical distance

We noticed in section 2 that supports were considered in the set $\mathcal{M}$ only if their distance to the associated random plane was less than a critical distance d. This distance may be seen as the standard deviation of the supports with regard to the 3D plane. d is therefore defined for each cluster $\mathcal{C}$ as proportional to the final residual square root of a least square fitted plane estimated from the entire laser points $\{P\}$ within $\mathcal{C}$. If $\{P'\}$ is the orthogonal projection of $\{P\}$ onto the fitted plane, then

$$d = \sqrt{\sum_{P \in \mathcal{C}} ||P - P'||^2} \qquad (2)$$

3.2.2 The number of draws

The number of draws to be performed depends on the distribution $p(\overrightarrow{n})$ of the normal vectors within a cluster (where $\overrightarrow{n} = \begin{pmatrix} n_x \\ n_y \\ n_z \end{pmatrix}$ are considered as three random variables), and especially on the probability w that any selected point is an inlier (equation 1). Following the definition of a probability and considering that the final plane will be close to the mathematical expectation $\mathbf{E}(\overrightarrow{n})$ of the distribution, w satisfies:

$$w = \int_{\mathbf{E}(\overrightarrow{n})-\overrightarrow{\sigma}}^{\mathbf{E}(\overrightarrow{n})+\overrightarrow{\sigma}} p(\overrightarrow{n})\, \mathrm{d}\overrightarrow{n} \qquad (3)$$

We may assume that the three random variables n_x, n_y, n_z are independent to write:

$$w = \int_{\mathbf{E}(n_x)-\sigma_{n_x}}^{\mathbf{E}(n_x)+\sigma_{n_x}} p_x(n_x)\, \mathrm{d}n_x . \int_{\mathbf{E}(n_y)-\sigma_{n_y}}^{\mathbf{E}(n_y)+\sigma_{n_y}} p_y(n_y)\, \mathrm{d}n_y . \int_{\mathbf{E}(n_z)-\sigma_{n_z}}^{\mathbf{E}(n_z)+\sigma_{n_z}} p_z(n_z)\, \mathrm{d}n_z . \qquad (4)$$

$p_x(n_x)$ (resp. $p_y(n_y), p_z(n_z)$) is explicitly calculated as the derivative of the empirical probability density function F_{K_x} (resp. F_{K_y},F_{K_z}) with:

$$F_{K_x}(x) = \begin{cases} 0 & \text{if } x < \mathbf{inf}\, n_i \\ \frac{n_i}{K_x} & \text{if } n_i < x \leq n_{i+1} \\ 1 & \text{if } x > \mathbf{sup}\, n_i \end{cases} \qquad (5)$$

where n_i is the proportion of values less than x and K_x (resp. K_y,K_z) the number of realizations of the random variable n_x (resp. n_y, n_z).

4 Results and Discussion

The algorithm was tested onto a laser data set acquired over the city of Amiens, France, by the company TopoSys©. This firm owns a self-made lidar acquisition system, which is composed of two rigid blocks of optical fibers (emission and reception of laser pulses). The ground pattern of laser impacts is strongly irregularly distributed. The spatial density of the point cloud is roughly one point every $10\,cm$ along the flight track and one point every $1.2\,m$ in the cross-track direction. The density is 7.5 points$/m^2$.

Results presented in figure 2(b) (resp. 2(d)) have been computed with the following parameters: normals are calculated over a $0.15\,m$ resolution grid (resp. $0.30\,m$) onto a circular neighborhood of $2\,m$ radius, the minimum number of laser points within a cluster is set to 30. Finally, each cluster must be composed of at least 25 pixels to be considered. Our methodology is slightly less general than a classical RANSAC which provides, whatsoever, relevant planes within the point cloud after theoretically an infinite number of iterations. Nevertheless, it is particularly interesting to take benefit of the specific geometry of buildings which make the success of the method dependent on the correctness of the normal vector map. A visible artifact of such dependence is that roof facets are retrieved by patches (see figure 2(b)). This can be treated a posteriori with a plane fusion algorithm. However, if we consider laser data as auxiliary data sources, these planar primitives bring strong geometric constraints to advanced reconstruction strategies.

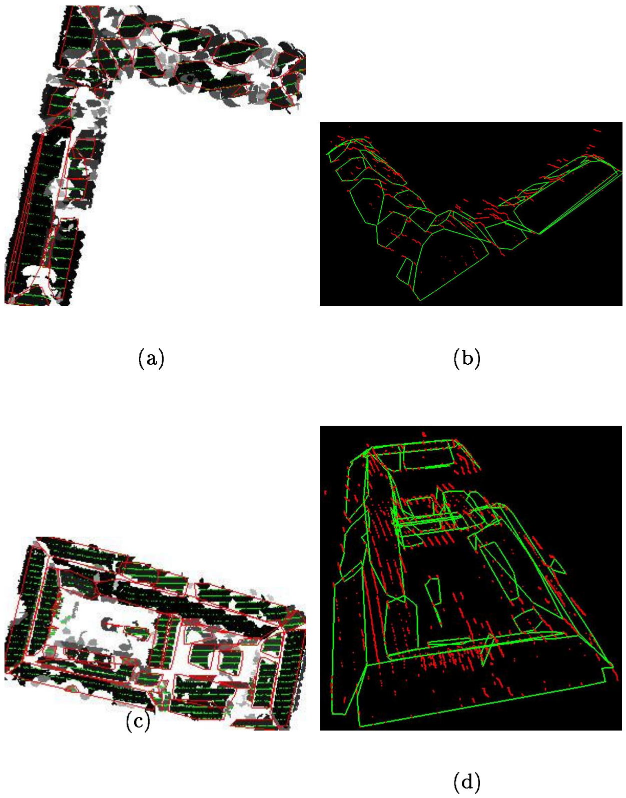


Figure 2: (a) and (c) are the cluster images coded in gray level whereon laser points have been projected (green points) as well as retrieved facets (red polygons). (b) and (d) are the 3D representation of roof facets (green polygons). Red points are the residuals of laser points which have to be considered as support of any plane.

5 Conclusion

We have presented in this article a strategy for detecting 3D planar primitive from airborne laser data. It is based on a random sample consensus driven with information concerning normals of the 3D scene. The main contribution with regard to a traditional RANSAC approach consists of minimizing the number of random draws by analyzing the distribution of the normal vectors within a cell of an EGI. Results are promising and will be soon integrated into a joint segmentation algorithm of aerial images and laser data.

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