

AN IMPLICIT REGULARIZATION FOR 3D BUILDING ROOFTOP MODELING USING AIRBORNE LIDAR DATA

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ABSTRACT:

This paper proposes a new algorithm to generalize noisy polylines comprising a rooftop model by maximizing a shape regularity (orthogonality, symmetry and directional simplicities). The nature of remotely sensed data including airborne LiDAR often produce errors in localizing salient features (corners, lines and planes) due to weak contrast, occlusions, shadows and object complexity. A generalization or regularization process is well known algorithm for eliminating erroneous vertices while preserving significant information on rooftop shapes. Most of existing regularization methods achieves this goal base on a local process such as if-then rules due to lacking global objective functions or mainly focusing on minimising residuals between boundary observations and models. In this study, we implicitly derive rules to generate local hypothetical models. Those hypothesized models produce possible drawings of regular patterns that given rooftop vectors can possibly generate by combining global and local analysis of line directions and their connections. A final optimal model is globally selected through a gradient descent optimization. A BSP (Binary Tree Partitioning)-tree was used to produce initial rooftop vectors using ISPRS WGIII/4's benchmarking test sites in Veihngen. The proposed regularization algorithm was applied to reduce modelling errors produced by BSP-tree. An evaluation demonstrates the proposed algorithm is promising for updating of building database.

1. INTRODUCTION

In recent years, there has been increasing demands to have 3D rooftop models as emerging technologies such as GeoWeb, LBS (Location Based System) and MAR (Mobile Augmented Reality) have been demonstrated potential applications. These include urban management, planning and development (Scherer and Schapke 2011, Yu et al. 2010), environmental management (Kurakula 2007), tourism (Glander and Dollner 2009), telecommunications (Wagen and Rizk 2003), transportation and navigation, public safety. Reconstructing 3D rooftop models using remotely sensed data should deal with the presence of the "missing data". Assume that a rooftop is comprised of a set of polygons (planar features), which are inter-linked with lines (linear features). It is generally unknown as *a priori* knowledge: how the shape of a building of interest is (shape prior); how many features (polygons and lines) are required to model it; what topological rules (relations) are associated with the model. Moreover, the signal-to-noise ratio is always unknown, which causes difficulties to predict fragmentary level of modelling cues (features) extraction. Knowing a building shape prior would make ease all difficulties in rooftop modelling since it provides compensate the knowledge on "missing features" and "missing relations". However, obtaining such rich priors is rare case in practice: even generalizing the shape prior into a semantic level (how to describe a shape) would be hard problem. To overcome this limitation, the parametric modelling approach (You et al. 2003, Verma and Kumar 2006, Teo 2008, Frederik et al. 2012) poses it as a model selection problem. That is, the method assumes that multiple shape priors (flat, gable, hip and etc) are given in advance. Thus, the rooftop problem is now translated into determining which prior (model template) would be the best fit to given observations (surface model and features) and estimating associated model parameters. The method would be promising if right modelling templates and sufficient observations are given for reconstructing rooftop models.

However, a most challenge in this approach might be faced when a building of interest is comprised of N numbers of sub-models; unfortunately this would be the case in complex urban setting. In contrast to the parametric modelling approach, a generic modelling (Rottensteiner 2003, Alharty and Bethel 2004, Sampath and Shan 2007, Sohn, et al. 2008) is based on a bottom-up vision process, which recovers the missing data mainly relying on extracted features from given data. This could limit to access to building shape priors, which causes more difficult problems in recovering missing features and their topological relations. However, it would be adaptive to delineate more complex shapes by avoiding the use of shape priors. However, the missing features is an inevitable. The generic modelling method should deal with recovering the features missed during its reconstruction process. Sohn et al. (2008) proposed a BSP (Binary Space Partitioning)-tree as for solving the missing data problem in a generic modelling approach. It demonstrated its success to produce building models, but also discussed its limitations of incorrectly producing topological links amongst modelling features. This paper proposes a new method to rectify the topological errors produced by Sohn et al. (2008)'s BSP algorithm. The proposed method is designed mainly based on part of cartographic regularization algorithms (Douglas and Peucker, 1973; Weidner and Forstner, 1995; Ameri, 2000; Sampath and Shan, 2007), which eliminates erroneous vertices, while preserving significant information of building shape. Our method was motivated by Weidner and Forstner (1995)'s work. We consider the resulting vectors from BSP as noisy model boundaries. The proposed algorithm progressively rectifies them based on Minimum Description Length (MDL).

2. METHODOLOGY

This paper proposes a new generative modelling approach to reconstruct 3D building model and rectify their geometric and

topological errors amongst modelling features. The important aspect of the proposed method is to determine an optimal shape regularity (orthogonality, symmetricity and simplication) during modelling process. This is achieved by testing hypothesized regularizing models. Fig. 1 depicts the whole work flow for proposed modelling algorithm.

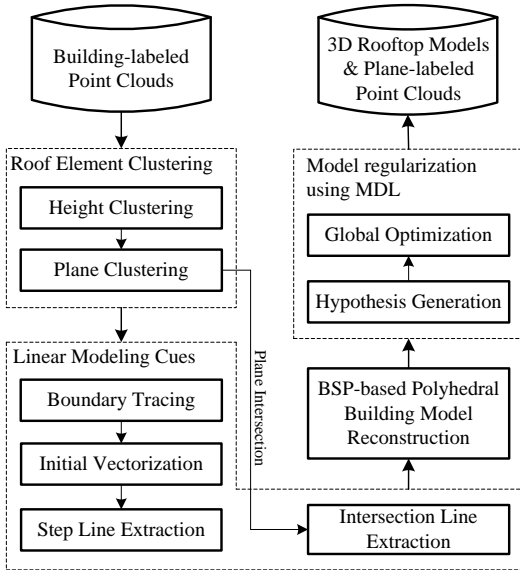


Figure 1. Illustrated workflow of proposed 3D rooftop modelling process.

2.1 Roof Element Clustering

Buildings exhibit a range of rooftop types and a complex combination of building parts including roof superstructures. This places some limitations on extracting meaningful modelling cues directly from building-labelled point clouds. To reduce the complexity in feature extraction, the first step is to partition building points into each homogeneous rooftop region based on two similarities: height and plane similarity. In the height clustering, let $R = \{P_i \mid i=1,2,\dots,n\}$ represent a rooftop region with n numbers of points and consists of m numbers of height segments $R = \{S_1, S_2, \dots, S_m\}$. Height difference δh_i at each point is computed from its neighbour points connected in Triangular Irregular Network (TIN). If δh_i is less than a certain threshold, P_i belongs to the same height cluster. As a result, the segments satisfy with the property $R = \bigcup_{i=1}^m S_i, S_i \cap S_j = \emptyset, \forall i \neq j$. Once a set of height clusters is extracted, the plane clustering process is performed over each height cluster S_i , which is decomposed of k numbers of plane clusters $\{\pi_1, \pi_2, \dots, \pi_k\}$. We adopt random sample consensus (RANSAC) algorithm to obtain the best plane segments as suggested in many previous studies (Ameri and Fritsch 2000, Tarsha et al. 2008). First, three points are randomly selected. These points are used as seed points to generate an initial plane segment. Then, more points are captured by using a tolerance distance ζ between π_i and P_j and plane parameters (a,b,c) are updated recursively. This process continues until each plane has the maximum probable inlier points and all points that belong to S_i are assigned into plane clusters.

2.2 Linear Modelling Cue Extraction

After plane segments are detected, two different types of line primitives (intersection and step lines) are extracted. The intersection line is simply generated by intersecting between adjacent planar segments. To extract step lines, plane boundary

points are traced. This process is accomplished by using a modified convex-hull method, in which the topology between member points is defined based on TIN structure. Then a local height discontinuity is investigated to detect step edge pixels among boundary points between adjacent planes. Then the process of initial vectorization is performed to generate linear modelling cues. Given a sequence $D = \{P_1, \dots, P_n\}$, $P_i \in \mathbb{R}^2$ of n boundary points in the plane, the polyline segments are formed as a successive chain $C = \{\overline{P_1 P_2}, \dots, \overline{P_{n-1} P_n}\}$. The initial simplification of polylines is performed by obtaining a chain C' with m fewer segments. To achieve this goal, we adopt Douglas-Peucker (DP) algorithm which has been recognized as an effective line simplification method (Ramer, 1972). By using a line segment $\overline{P_i P_j} = \{1 \leq i, j \leq n \mid i \neq j\}$, if the norm from a vertex to $\overline{P_i P_j}$ is less than tolerance $\zeta > 0$, the vertex is removed, while a vertex shows the maximum norm is determined as an inlier point to the line segment $\overline{P_i P_j}$. This procedure continues until the norms of remaining vertices are less than ζ . Note that the degree of irregularity to be handled in DP algorithm depends on ζ . DP is effective to eliminate erroneous vertices in a simple manner. However, it does not provide a mechanism to make given polylines being regular shape patterns, that is maximizing Gestaltic laws (orthogonality, parallelity and symmetricity) in addition to simplication. In later sections, we propose these multiple objectives can be achieved through MDL (Minimum Description Length).

2.3 BSP-based Polyhedral Building Model Reconstruction

Once all modelling features (lines and planes) are extracted as described in the previous sections, topological relations amongst modelling features for each height segment are constructed using Sohn et al. (2008)'s algorithm. Sohn et al. (2008) concentrated on a topological construction with fragmentary modelling features. They proposed BSP-tree as its solution to globally recover modelling topology from incomplete features. A partitioning optimum is achieved by maximizing planar homogeneity produced through a recursive intersection between lines and associate planes. The process generates a hierarchical binary tree, in which each node (terminal) represents planar polygons that provides the information of topological relations among its adjacent planar segments. A final model is produced to combine similar planar segments in BSP-tree.

2.4 Model regularization using MDL

A most bottleneck of BSP-tree for rooftop modelling is caused by an "accidental cause" that occurs in line-line intersection for constructing planar topological relations. That is, an error in line feature inherited from line extraction process might lead to errors in geometry and under-/over-generation of vertices in rooftop models. Thus, it is required to rectify those errors. It could be done by line simplification algorithm. However, our goal is to make given rooftop vectors being a regular shape pattern in addition to eliminating erroneous vertices; combining line simplification with regularization. A shape regularity is defined as being as shape pattern that shows orthogonal, parallel and symmetric relations between lines as similar to Gestaltic laws. This prior knowledge on shape regularity is often implemented using a set of deterministic rules such as "IF-THEN" rules. However, in our approach, the shape regularity means more than pre-specified rules, but implicitly derive rules (possible shape regularity) with given initial rooftop vectors. The proposed method does not require pre-determined threshold constraining the regular shapes, rather determining optimal shape through MDL-based model selection process.

