IMPROVING AUTOMATIC RECONSTRUCTION OF INTERIOR WALLS FROM POINT CLOUD DATA

E. Maset*, L. Magri, and A. Fusiello

DPIA – University of Udine, Via delle Scienze, 206 – Udine, Italy

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1. INTRODUCTION

Generating 3D indoor models from point clouds is an active research topic, with several applications in fields such as navigation, emergency response, building maintenance and monitoring (Zlatanova et al., 2013). Since manual reconstruction of indoor environments is an expensive and time consuming process, in the last years several procedures have been proposed for the automated generation of indoor models from data acquired by terrestrial or mobile laser scanners (Wang et al., 2017, Previtali et al., 2018b).

The core of any method for indoor scene reconstruction is represented by the robust extraction of multiple geometric primitives from noisy and outlier-contamined measurements deriving from the presence of furniture causing clutter and complex walls arrangements that determine occlusions.

Among the works dealing with indoor modelling, three different classes can be identified, according to the searched primitives (Previtali et al., 2018a): linear, planar or volumetric. The method presented in (Magri and Fusiello, 2018) falls in the first category, where the overall structure of the environment is extracted by fitting lines to the main building features, using *Min-hashed J-Linkage* as a multi-model fitting technique. The aim of this work is to propose an improved version of (Magri and Fusiello, 2018), taking into account the points distribution along the vertical axis, avoiding the usage of several manually tuned thresholds and leveraging on a cell-complex subdivision of the plane to enhance the topological correctness of the result.

2. PROPOSED METHOD

The first part of the method closely follows the procedure proposed in (Magri and Fusiello, 2018). The algorithm reduces the 3D point cloud to a set of sampled planar points, referred to as *wall samples*, enriched with information about their local orientations. An histogram of point heights is computed and the floor/ceiling bins are identified as the bottom-most and top-most local maxima. Planes are fitted via Iterative Reweighted Least Squares on the points belonging to these bins, the corresponding inliers are labeled as floor and ceiling respectively and are then discarded from further analysis (and the histograms are updated accordingly). The rest of the 3D points are projected onto the floor plane which is uniformly discretized in a grid of ground-cells.

If enough points (default is 10) fall inside a ground-cell, their median position is taken as a *wall sample* representative for that cell and a normal vector is locally estimated using Principal Component Analysis.

*Corresponding author: maset.eleonora@spes.uniud.it

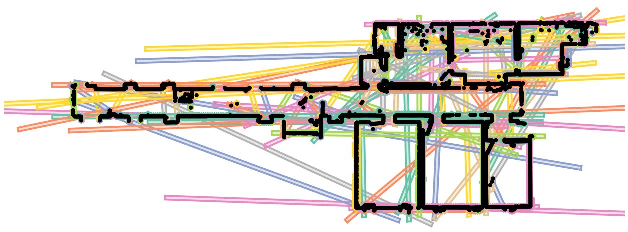


Figure 1. Lines extracted by Min-hashed J-Linkage, depicted with their inlier band.

The next step consists in organizing the wall samples into linear structures, exploiting the Min-hashed J-Linkage algorithm and taking into account also their normal vectors. An example of the result is illustrated in Fig. 1. This stage requires the definition of an inlier threshold ϵ: a point belongs to the supporting set of a fitting line if its residual is below this threshold.

From this point we depart from (Magri and Fusiello, 2018) and propose the following procedure.

The lines yielded by Min-hashed J-Linkage are associated to wall samples that come not necessarily from actual wall, but also from furniture and clutter, which can negatively affect the results. For this reason, we exploit the point heights histogram associated to each wall sample to cluster them into three classes corresponding to uniform (U), low-thicker (L) and high-thicker (H) histograms (see Fig. 3), and prune the J-Linkage result.

The histogram is first binarized (empty cell → 0) then clustering is performed using *Hamming* distance and *k-means* with three seeds corresponding to the classes archetypes (result is shown in Fig. 3). Then, we deem as outliers those lines that are supported by a majority of L or H samples. The remaining lines are scrutinized for outliers with a *inward testing* procedure (Davies and Gather, 1993): samples that are classified as L or H are

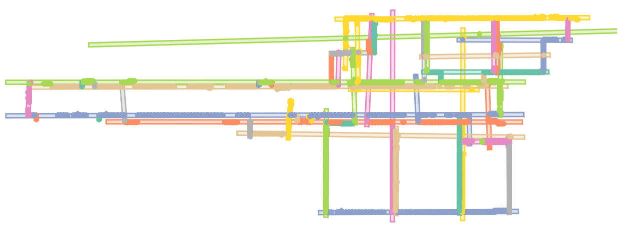
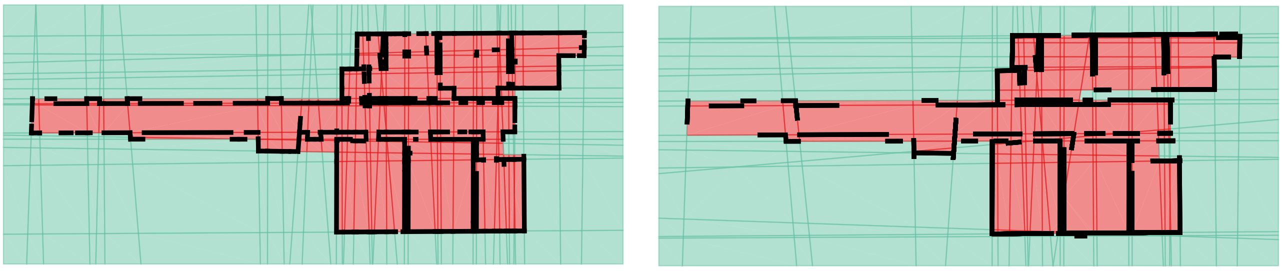


Figure 2. Results of the vanishing point clustering. Lines that do not conform to the dominant orientations have been discarded.

(a) (b)

Figure 3. Classification of the wall samples (a) into U/L/H with examples of histograms (b).



(a) (b)

Figure 4. Blueprints obtained with (a) the proposed method and (b) the method by (Magri and Fusiello, 2018).

removed one at a time and the line is fitted on the remaining ones. If the residual of the removed sample is greater that ϵ, it is considered as an outlier and removed from the supporting set of that line.

Subsequently, we discard the lines that do not conform to the so called *Manhattan Word* assumption. Following (Magri and Fusiello, 2018), lines are grouped by fitting vanishing points with J-Linkage and retaining only the lines that belong to the two clusters with the larger cardinality, as shown in Fig. 2. Aligning the dominant directions with the axes greatly simplifies subsequent computations.

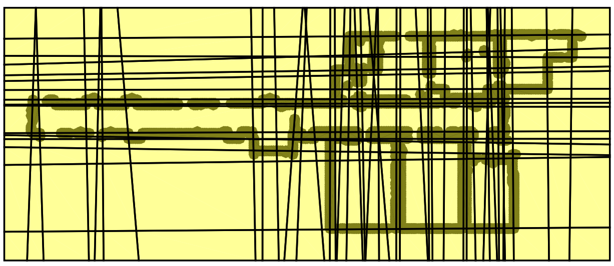


Figure 5. Cell-complex determined by the line arrangement.

To finally group wall samples into segments, it is convenient to exploit the subdivision of the plane induced by the arrangement of the detected lines, formally defined as a 2D *cell-complex* and stored in a *Doubly Connected Edge List* (DCEL), a structure commonly used in computational geometry that consists of vertices, edges, and faces (see Fig. 5). To each edge of the DCEL we assign the wall samples that i) are included in the supporting set of the line to which the edge belongs and ii) whose coordinates fall in the interval defined by the edge's endpoints. Then we project these wall samples onto the corresponding edge and order them.

In this stage, in order to fill gaps caused by the presence of furniture and clutter, we consider the outlier lines previously discarded (because mainly supported by H or L samples) that are aligned with the dominant orientations. Their samples are then projected onto the closest edge along the direction orthogonal to the line itself, within a threshold of 60 cm.

Following the linear order along an edge, a new segment is instantiated when the distance between two consecutive points exceeds a threshold, computed for each line l as follows:

$$t(l) = \bar{d} + 3.5 \ \mathrm{med}_i |d_i - \bar{d}|$$

where d_i is the distance between consecutive points belonging to the supporting set of the line l and $\bar{d} = \mathrm{med}_i(d_i)$.

In this way, we constructed a hierarchy: `point` $\rightarrow$ `segment` $\rightarrow$ `edge` $\rightarrow$ `line` where all the maps are injective. As a result, thanks to the subdivision of the wall segments induced by the cell-complex, the topological correctness of the segments is guaranteed, i.e., there are no intersections other that at the endpoints (like T-junctions or overlaps). Moreover, topological relations can be fruitfully exploited in subsequent steps, e.g., to identify internal and external spaces or to group cells into clusters that represent rooms.

3. PRELIMINARY RESULTS

In Fig. 4(a) we show the blueprint generated with the proposed pipeline for the first dataset of the ISPRS benchmark (Khoshelham et al., 2017). Comparing the result with the one obtained by (Magri and Fusiello, 2018), illustrated in Fig. 4(b), one can notice the higher accuracy and completeness reached by the novel method.

4. DISCUSSION

We proposed a variation of the method presented in (Magri and Fusiello, 2018), that has the merit of producing more accurate results (in particular by increasing completeness), and greatly reducing the need for user-defined thresholds. With respect to this issue we have been following these principles, in cascade: i) to avoid free parameters at all; ii) to make them data-dependent; iii) to make user-specified parameters intelligible and subject to an educated guess. This guarantees the processing to be completely automatic in the majority of cases.

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