Enhanced Reconstruction of Architectural Wall Surfaces for 3D Building Models

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Abstract

The reconstruction of architectural structures from 3D building models is a challenging task and a lot of research has been done in recent years. However, most of this work is focused mainly on reconstructing accurately the architectural shape of interiors rather than the fine architectural details, such as the wall elements (e.g. windows and doors). We focus specifically on this problem and propose a method that extends current solutions to reconstruct accurately severely occluded wall surfaces.

CCS Concepts

• ***Theory of computation*** → ***Computational geometry;*** • ***Computing methodologies*** → ***Point-based models;***

1. Introduction

During the last decade, the demand for semantically rich 3D building models (i.e. Building Information Models, BIMs) has drastically increased. Although most of the times a raw blueprint with wall indications and other rough floorplan information is provided, the actual details of building's architectural permanent elements (e.g. locations and dimensions of windows or doors) is not always available or may not be up-to-date from the initial design time. However, their accurate recovery is of high importance for BIM applications, since the highly added value in BIMs is originated, not only from the building's architectural shape, but mainly from the fine architectural details derived e.g. from the wall elements.

Existing methods typically rely on heuristics, prior knowledge and machine learning [OVWK16, BVVG16, ACW17] for their reconstruction, while others combine cues from images and 3D range data [DML*14, SWF16]. These methods, however, introduce many limitations due to their nature and fail to reconstruct wall surfaces with complex or irregular window frames, especially under high levels of occlusions. Approaches focusing only on the reconstruction of wall surfaces have been also proposed [MP17], although they present inaccuracies and erroneous interpretations under some challenging but common scenarios.

In this work, we make specific interventions to state-of-the-art which allow better reconstruction results under severely occluded wall surfaces, automatic semantization and extended applicability. Specifically, we adopt the method in [MP17] and replace its line model fitting and clustering approach with a new one, we add a new regularization term in its graph-cut segmentation approach to enforce spatial consistency, we introduce a highly efficient post-processing stage for refining the wall surface segmentation and, finally, we annotate the reconstructed wall elements, extracting better and semantically enriched wall surfaces than [MP17]. Moreover, in contrast to previous methods, our approach do not require any manual tuning and do not rely on assumptions and additional imagery or depth data.

2. Wall Surface Reconstruction

Our pipeline takes as input the architectural shape of the indoor environment, extracts its wall surfaces and computes the α-shapes 2D polytope of their points similar to [MP17]. Next, a line model fitting method is applied to α-shapes boundaries for getting regularized boundaries. Although RANSAC is a good candidate and has been used in similar scenarios [OVWK16, MP17], due to the inherent uncertainties introduced by the structural composition of the α-shape (e.g. variations in boundary α-shapes during the union of the $d-dimensional$ balls depending on α value, on non-uniform density of points, etc.), RANSAC will not produce the most optimal results. Therefore, we used the PEARL multi-line model fitting method [IB12], which combines model sampling from data points as in RANSAC but using iterative re-estimation of inliers, formulates the model fitting problem as an optimization problem with a global energy function describing the quality of the overall solution.

Next, to favor alignment with the wall elements and reduce the complexity of wall surface partitioning, we use a clustering technique for segmenting the line space and assigning each line model to a set of mode (i.e. representative) line models. Although a global clustering approach such as mean-shift [OVWK16, MP17] is satisfactory for roughly estimating collinear wall directions and other coarse features in a building, the detection of fine scale features in small and nearby local inhomogeneous regions in the wall surface might lead to misalignments and erroneous reconstructions.

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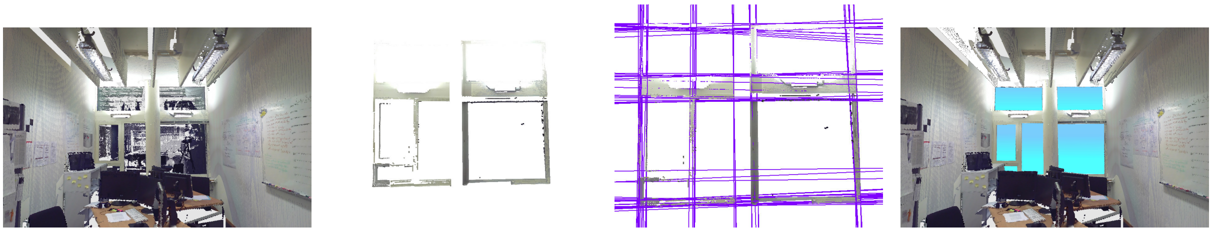

Figure 1: *Reconstruction results for a challenging room environment (left) which contains a highly occluded wall surface with many corrupted adjacent window frames (middle-left), the representative mode lines (middle-right), and the final reconstructed wall elements (right).*

Therefore, we propose a robust and feature-preserving line clustering technique, where each line model is associated with a weight derived by the number of α-extreme points that contributed to its estimation. To partition the line space, we set first a measure of spatial distance based on the maximum distance between the neighboring lines and the maximum angle of their normals, and then we evaluate all lines through a voting process inside a local neighborhood. The line that approximates better the local geometry is set as the representative mode line in the neighborhood and the weights from all other neighboring lines are assigned to it.

Similar to [MP17], we perform occlusion detection, while in the graph-cut segmentation stage we enforce spatial consistency between neighboring cells introducing to the n-links a new regularization weighting term $w_{r_{p,q}}$ to lower the cost of adjacent cells that are expected to belong to similar regions. This term is dependent on the coverage of each cell's edge by the α-extreme points is determined by performing an occupancy analysis on the cell edges. The resulted regularization term is then given by $\mathcal{R}_{bound_{p,q}} = (1 - w_{r_{p,q}}) \cdot \beta_r \; \forall p \neq q$ (0 otherwise), where the constant β_r is equal to the surface area of the associated cell. The final edge weights are then defined as $w_{p,q} = \kappa_n(\mathcal{R}_{dens} + \mathcal{R}_a + \mathcal{R}_{bound}) \; \forall p \neq q$ (0 otherwise) and the exact solution of the global minimum cut of the graph is computed from $E(f) = \sum_{p \in V} (w_p^{(s)} + w_p^{(t)}) + \sum_{\{p,q\} \in N_G} w_{p,q} \cdot T_{p \neq q}$ (see also [MP17]).

3. Post-Refinement and Semantization

To enhance further the reconstructed results and eliminate the erroneous cell classifications under extremely cluttered or occluded environments, we propose a post-refinement stage which relies on the contextual information of the cells. Intuitively, we want to identify the reliably (i.e. with high confidence) classified cells in the complex and replace the unreliably classified ones. To do so, we rely on Cellular Automata (CA) [VN66], which are algorithms that can operate on a lattice of sites (in our case, the cell complex) and update their state synchronously in discrete time steps according to local transition rules. Given the segmented cell complex, we consider the Moore neighborhood with radius $r = 1$ and the CA rule patterns illustrated in Fig. 2. In every transition rule, certain criteria such as the point density, label, total number of points and α-extreme points are evaluated and if fulfilled, the central cell's label is replaced by a neighboring label, otherwise it remains unaltered. The final wall elements are formed by merging adjacent cells with same labels.

In the last stage of our pipeline we semantically annotate the segmented wall elements based on contextual and geometric cues. Each wall element is evaluated against certain shape and positional criteria and gets a specific label from the label set $\{window, door\}$.

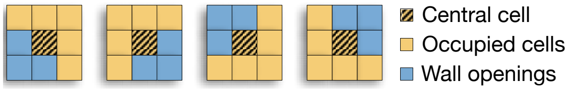

Figure 2: *CA rule patterns.*

4. Conclusions

We discussed the problem of reconstructing the architectural wall surfaces of complex indoor environments, showing how state-of-the-art could be extended to reconstruct efficiently wall elements with many corrupted window frames under high levels of clutter and occlusions. The evaluation of the proposed method is ongoing work and in the future we intend to incorporate the proposed extensions to a new reconstruction pipeline.

References

[ACW17] AMBRUS R., CLAICI S., WENDT A.: Automatic room segmentation from unstructured 3D data of indoor environments. *IEEE Robotics and Automation Letters 2*, 2 (April 2017), 749 – 756. 1

[BVVG16] BASSIER M., VERGAUWEN M., VAN GENECHTEN B.: Automated semantic labelling of 3d vector models for scan-to-bim. In *International Conference on Architecture and Civil Engineering* (04 2016), pp. 93–100. doi:10.5176/2301-394X_ACE16.83. 1

[DML*14] DÍAZ-VILARIÑO L., MARTÍNEZ-SÁNCHEZ J., LAGÜELA S., ARMESTO J., KHOSHELHAM K.: Door recognition in cluttered building interiors using imagery and lidar data. In *Proceedings International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences* (2014), vol. XL-5, pp. 203–209. 1

[IB12] ISACK H., BOYKOV Y.: Energy-based geometric multi-model fitting. *International Journal of Computer Vision 97*, 2 (2012), 123–147. 1

[MP17] MICHAILIDIS G.-T., PAJAROLA R.: Bayesian graph-cut optimization for wall surfaces reconstruction in indoor environments. *The Visual Computer 33*, 10 (October 2017), 1347–1355. doi:10.1007/s00371-016-1230-3. 1, 2

[OVWK16] OCHMANN S., VOCK R., WESSEL R., KLEIN R.: Automatic reconstruction of parametric building models from indoor point clouds. *Computers & Graphics 54* (February 2016), 94–103. 1

[SWF16] SUI W., WANG L., FAN B.: Layer-wise floorplan extraction for automatic urban building reconstruction. *IEEE Transactions on Visualization and Computer Graphics 22*, 3 (2016), 1261–1277. 1

[VN66] VON NEUMANN J.: *Theory of Self-Reproducing Automata*. University of Illinois Press, 1966. 2