Automatic Modeling of Planar-Hinged Buildings

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Figure 1: *a)* Our reconstructed planar-hinged buildings; b) with projective texture mapping, and c) pipeline: initial points, initial triangulation, Canny edge points, visualization of plane/hinge constraints, final model, with texture mapping.

Abstract

We present a framework to automatically model and reconstruct buildings in a dense urban area. Our method is robust to noise and recovers planar features and sharp edges, producing a water-tight triangulation suitable for texture mapping and interactive rendering. Building and architectural priors, such as the Manhattan world and Atlanta world assumptions, have been used to improve the quality of reconstructions. We extend the framework to include buildings consisting of arbitrary planar faces interconnected by hinges. Given millions of initial 3D points and normals (i.e., via an image-based reconstruction), we estimate the location and properties of the building model hinges and planar segments. Then, starting with a closed Poisson triangulation, we use an energy-based metric to iteratively refine the initial model so as to attempt to recover the planar-hinged model and maintain building details where possible. Our results include automatically reconstructing a variety of buildings spanning a large and dense urban area, comparisons, and analysis of our method. The end product is an automatic method to produce watertight models that are very suitable for 3D city modeling and computer graphics applications.

I.3.3 [Computer Graphics]: Picture/Image Generation—I.3.7 [Computer Graphics]: 3-D Graphics and Realism—

1. Introduction

3D city modeling has become extremely popular due to the increased number of computer graphics applications in the entertainment industry, urban planning, digital mapping, and virtual environments. However, the automatic modeling of large dense cities, including the robust recovery of sharp edges and planar features, and the creation of water-tight geometric models suitable for texture mapping and interactive applications remains elusive. Previous efforts have addressed our goal using one or more different input sources (e.g., LIDAR or image data), and from ground-level viewpoints, airborne viewpoints, or combinations thereof. We identify three key challenges: i) sampling completeness - obtaining samples from all surfaces is a daunting task typically addressed by either coalescing information from multiple

viewpoints or filling-in holes; for large-scale city modeling obtaining a full sampling of all surfaces using multiple viewpoints is impractical; ii) surface triangulation - in the presence of missing samples, generating a closed-triangulation can be hard for traditional triangulation methods which assume clean and near uniform sampling (e.g., [DGQ*12]); and iii) noise - in general recovering sharp edges and other surface features (e.g., planarity, circularity) is hard in the presence of significant noise.

Our approach addresses the sampling completeness, surface triangulation, and noise challenges by defining a class of buildings which supports sharp edges and planar segments and using a new framework to improve automatic building surface reconstruction. Coughlan and Yuille [CY99] defined Manhattan World (MW) buildings as a restricted subset of buildings consisting of exterior façade segments belonging to one of three orthogonal planes. Schindler and Dellaert [SD04] extended the Manhattan World assumption to Atlanta World (AW) which includes multiple groups of orthogonal vanishing directions. We further extend the assumption to arbitrary planar-hinged building models. A building's surface consists of arbitrary planar segments interconnected by linear (i.e., straight) hinges at any angle. This framework affords a more general class of buildings than MW or AW.

We demonstrate several automatically reconstructed buildings within $0.5 km^2$ in Boston (USA) using 135 aerial images.

Our main contributions include

- a framework that defines planar-hinged building models for modeling and reconstruction,
- an iterative algorithm to generate closed and complete buildings by using an energy-based metric to warp a Poisson mesh to one containing sharp edges and planar segments, and
- a novel approach to find hinges in an initial building model by using pre-filtered edge-detected images and a probabilistic model for defining the hinge planes and façade planes with spatially varying confidence values.

2. Related Work

Modeling and reconstruction of building structures within dense large cities has been addressed by a variety of works. From a purely modeling point of view, Vanegas et al. [VAW*09] describe a comprehensive summary. From an urban reconstruction standpoint, Musialski et al. [MWA*12] present a recent survey on general urban reconstruction methods. In our work, we use points, planes, and hinges obtained from image data. In principle, we can also apply our methodology to LIDAR data (e.g., Korah et al. [KMO11], Poulis and You [PY09], and Zhou and Neumann [ZN09]). While planarity might be exploited it is usually enforced by assuming predetermined roof types are present and ignoring building walls (i.e., 2.5D reconstruction).

For automatic reconstruction, some methods have made strong assumptions about the underlying geometry. For example, Furukawa et al. [FCSS09] and Vanegas et al. [VAB10] obtain robust reconstructions of fragments of MW building interiors and/or exteriors. [DIOHS08] extract highquality spline based features but assume a point cloud dense enough to apply RMLS (type of MLS, such as [ÖGG09]).

Several works assume buildings contain planar segments. For example, Lafarge and Mallet [LM11] focus on planar regions and on edges of a top-down 2.5D model using a complete dense point cloud. Chauve et al. [CLP10] determine planar regions and then extend the planes so as to indirectly find edges. They assume points in the same plane belong to the same spatially adjacent cluster. These approaches do not include our more general hinge concept and focus on 3D structures.



Figure 2: Plane reconstruction.

3. Planar-Hinge Modeling and Reconstruction

Our approach uses high-resolution aerial images captured from a multi-camera cluster flying over a city (courtesy of C3Technologies), approximate building outlines extracted automatically from OpenStreetMap (GIS data), and autoautomatically produces a 3D triangulated model.

3.1. Initial Model

First, we obtain a *dense 3D point cloud* and an initial *model triangulation* and *model vertices*. The aerial images observing a building are given to Bundler [SSS06] to obtain a sparse point cloud. Then, we use CMVS [FCSS10] in combination with PMVS [FP07] to generate a dense 3D point cloud. The dense 3D point cloud is used to generate an initial model triangulation using Poisson surface reconstruction [KBH06]. Poisson surface reconstruction is able to generate a watertight closed mesh even in the presence of significant missing surface samples. However, the reconstruction generates a new set of approximating vertices, which we call the *model vertices*.

3.2. Plane Construction

Next, we find the most probable planar segments in the building's dense 3D point cloud. Initially, we smooth the normals estimated by CMVS using a normalized (based on the confidence values calculated by CMVS) bilateral-filter. Then, we find planar segments in the point cloud by growing regions based on point color and normal similarity and use random sample consensus (RANSAC) to determine the plane per region. Our method uses as region starting seeds the most densely-sampled 3D point cloud regions and successively adds points to regions based on normal similarity and distance measurements. After region growing, another pass regroups the regions that form the same plane but are not contiguous (Fig. 2a). Then, we re-run RANSAC to find the most probable plane per group (Fig. 2b). With just a few hundred iterations, the algorithm converges quickly and with a relatively small error (i.e., 5 cm. for up to 200m. high buildings). To preserve small geometric details, we partition the points in each of the aforementioned planar groups into a



Figure 3: Hinge reconstruction.

set of grid cells (Fig. 2c) and determine which cells contain points most likely belonging to the plane (Fig. 2d).

3.3. Hinge Construction

Using the input images with a Canny edge detector applied, we run CMVS and PMVS again to generate the building's edge 3D point cloud (i.e., 3D points reconstructed only on the edges of the building) (Fig. 3a). A hinge implies points forming a 3D line segment from location A to location B. There should be points approximately uniformly distributed within a cylinder from A to B and with a small radius r. To find candidate cylinders, we set each point in the cloud as a potential location A and search for a point B such that there are points contained within the cylinder from A to B. When a candidate cylinder is found, it is extended along its axis in both directions until there are no more points in the extended directions (Fig. 3b). Nearby cylinders with similar central axis directions are grouped. Then, we use RANSAC to find the most probable 3D line segment within each cylinder group (Fig. 3c). To find the planes adjacent to each 3D line segment, we partition the line segment and for each partition analyze the corresponding points in the building's dense 3D point cloud within the line segment's cylinder. We fit a single plane to all points in the cylinder segment. Then, we divide the points into two subgroups using the plane perpendicular to the fitted plane. We now fit a plane to each subgroup. If the two fits each have a small error (e.g., 5 cms or less), we have found the two local building surface planes. The result is a set of hinges over the building surface, each being a 3D line segment and two adjacent planar regions (Fig. 3d).

4. Model Reconstruction

In this process, we modify the model so as to better satisfy the plane and hinge constraints calculated with the 3D point clouds. Each hinge is divided into segments and each segment attracts model vertices within an action radius to its center line segment and to each of the hinge planes. In addition, each plane constraint also pulls model vertices towards the corresponding plane. In summary, the new position p_{i+1} of a point is calculated from p_i as:

$$p_{i+1} = p_i + \sum_{s \in H_l} \frac{(s-p_i)k}{\|s-p_i\|^2} + \sum_{f \in H_p} \frac{(f-p_i)k \cdot \delta}{\|f-p_i\|^2} + \sum_{c \in H_p} \frac{(c-p_i)k \cdot \gamma}{\|c-p_i\|^2}$$

where s is the center of each hinge line segment, k is a spring constant, f is the center of each hinge plane, δ =1 when the point lies within the action radius of the hinge plane and 0 otherwise, c is the center of each plane cell, and γ is the dot product of the grid cell normal with the direction of the point to the center of the plane.

5. Result and Analysis

Our system is implemented in C++, uses Qt/Boost/OpenCV/PCL, and runs on a desktop PC. We use images in five viewing directions of resolution 5616 x 3744 in order to reconstruct 20 buildings. The following table shows the average computation time for one building:

Bundler	PMVS	Hinge	Plane	Recons.
18 min	20 min	5 min	2 min	1 min



Figure 4: Triangulation Comparison.

Figure 4 shows the model reconstruction using one of four different triangulation algorithms. Poisson reconstruction generates a watertight closed model of the cloud point (4a). Marching cubes RIMLS reconstruction [ÖGG09] is qualitatively similar to the one generated by Poisson reconstruction, however it is not guaranteed to be closed and has many discontinuities (4c). Grid Projection reconstruction [LLP*10] is not able to fill holes (4b). Greedy projection triangulation [MRB09] produces reconstructions quickly but is very sensitive to noise and holes (4d).



Figure 5: Our Results vs. Poisson Reconstruction.



Figure 6: Results after using planes and hinges.

Figure 5 shows the improvement of our system as compared to a naïve Poisson reconstruction. Our system recovers sharper edges and corners using the hinge and plane constraints. In particular, the plane constraint significantly eliminates aberrations within facades. The hinge constraint improves the sharpness of the edges and corners (top) and can make incorrect geometry disappear (bottom).

Figure 6 shows the successive improvements of hinge and plane constraints. The initial model reconstruction has dull edges and perturbations in the supposedly flat parts due to lack of points and presence of noise (6b). Plane logic flattens the area, making the building more rectilinear (6c). Hinge logic brings improved geometric details to the building and creates sharper edges where detected (6d).

Figure 7 shows for two building examples the Hausdorff Distance between Poisson surface and our final model. In the already flat areas, the improvement is small (red), but in the areas where the error is big (e.g., missing samples), our system improves the model significantly with surface displacements of up to 8 meters.

6. Conclusions and Future Work

We have presented an automatic framework to model and reconstruct buildings using a planar-hinge model. We create complete and closed models. As future work, we will incorporate knowledge of roads, sidewalks, and other urban structures, merge other data sources (e.g., LIDAR), and experiment with faster GPU implementations.

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Figure 7: Surface displacement caused by our method.

References

- [CLP10] CHAUVE A.-L., LABATUT P., PONS J.-P.: Robust piecewise-planar 3d reconstruction and completion from largescale unstructured point data. *IEEE CVPR* (june 2010). 2
- [CY99] COUGHLAN J., YUILLE A.: Manhattan world: compass direction from a single image by bayesian inference. *IEEE ICCV* (1999). 1
- [DGQ*12] DEY T. K., GE X., QUE Q., SAFA I., WANG L., WANG Y.: Feature-preserving reconstruction of singular surfaces. *Comp. Graph. Forum* (2012). 1
- [DIOHS08] DANIELS II J., OCHOTTA T., HA L. K., SILVA C. T.: Spline-based feature curves from point-sampled geometry. Vis. Comput. (2008). 2
- [FCSS09] FURUKAWA Y., CURLESS B., SEITZ S. M., SZELISKI R.: Reconstructing building interiors from images. *IEEE ICCV* (2009). 2
- [FCSS10] FURUKAWA Y., CURLESS B., SEITZ S., SZELISKI R.: Towards internet-scale multi-view stereo. *IEEE CVPR* (2010). 2
- [FP07] FURUKAWA Y., PONCE J.: Accurate, dense, and robust multi-view stereopsis. *IEEE CVPR* (2007). 2
- [KBH06] KAZHDAN M., BOLITHO M., HOPPE H.: Poisson surface reconstruction. Eurographics symposium on Geometry processing (2006). 2
- [KMO11] KORAH T., MEDASANI S., OWECHKO Y.: Strip histogram grid for efficient lidar segmentation from urban environments. *IEEE CVPRW* (2011). 2
- [LLP*10] LI R., LIU L., PHAN L., ABEYSINGHE S., GRIMM C., JU T.: Polygonizing extremal surfaces with manifold guarantees. ACM Symp on Solid and Physical Modeling (2010). 3
- [LM11] LAFARGE F., MALLET C.: Building large urban environments from unstructured point data. *IEEE ICCV* (2011). 2
- [MRB09] MARTON Z. C., RUSU R. B., BEETZ M.: On fast surface reconstruction methods for large and noisy point clouds. *IEEE ICRA* (2009). 3
- [MWA*12] MUSIALSKI P., WONKA P., ALIAGA D. G., WIM-MER M., VAN GOOL L., PURGATHOFER W.: A survey of urban reconstruction. *Eurographics STAR* (2012). 2
- [ÖGG09] ÖZTIRELI C., GUENNEBAUD G., GROSS M.: Feature preserving point set surfaces based on non-linear kernel regression. *Eurographics* (2009). 2, 3
- [PY09] POULLIS C., YOU S.: Automatic reconstruction of cities from remote sensor data. *IEEE CVPR* (2009). 2
- [SD04] SCHINDLER G., DELLAERT F.: Atlanta world: an expectation maximization framework for simultaneous low-level edge grouping and camera calibration in complex man-made environments. *IEEE CVPR* (2004). 2
- [SSS06] SNAVELY N., SEITZ S. M., SZELISKI R.: Photo tourism: exploring photo collections in 3d. ACM SIGGRAPH (2006). 2
- [VAB10] VANEGAS C., ALIAGA D., BENES B.: Building reconstruction using manhattan-world grammars. *IEEE CVPR* (2010). 2
- [VAW*09] VANEGAS C. A., ALIAGA D. G., WONKA P., MÜLLER P., WADDELL P., WATSON B.: Modeling the appearance and behavior of urban spaces. *Eurographics* (2009). 2
- [ZN09] ZHOU Q.-Y., NEUMANN U.: A streaming framework for seamless building reconstruction from large-scale aerial lidar data. *IEEE CVPR* (2009). 2