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Template-based Point Cloud Modeling for Building Model

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***Abstract*—**We introduce a novel template-based modeling technique for 3D point clouds sampled from unknown buildings. The approach is based on a hierarchy algebraic template to fit noisy point clouds with sharp features. In the hierarchy template, the first-level, i.e., the lowest-level, contains three kinds of primitive geometries: plane, sphere, and cylinder. These primitive geometries are represented in algebra form. In the higher levels, some simple shapes are constructed by combining these primitive geometries, and the simple shapes can are further joined to form the final template model. In the fitting process, different to the general approaches which are intrinsic an iterative fitting process, we fit point clouds by directly solving a least-square linear system. This makes the approach efficient and robust in the point cloud modeling. Furthermore, some geometric constraints are taken into account in the fitting process for the purpose of increasing modeling accuracy. The experiment results show that the modeling accuracy is improved by integrating the geometric constraints in the fitting process, and the proposed template-based fitting is robust, in terms of withstanding noises and preserving sharp features, than the approaches based on implicit surfaces.

I. INTRODUCTION

Digital scanning devices such as LiDAR (Light Detection and Ranging) have recently become affordable and available. They are capable of acquiring high-accuracy and high-resolution point clouds. Thus, the techniques for point cloud modeling have received increasingly attentions. As the approaches reconstruct the point clouds, they face a common problem: how to handle the point clouds with the inherent noises. It will be especially challenge in handing point clouds that contains sharp features (for instance, the point cloud sampled from buildings in the city) since noises and sharp features are ambiguous mentioned in [1]. Most modeling techniques are based on constructing an implicit surface to fit point cloud [2-10,21,22]. Comparing to the topology-based reconstruction approaches [11,12,18-20], which are only able to handle data without noises, the implicit surface approaches that fit with a smooth function have the ability of handle noisy input. However, this also cause some important sharp features are smoothed.

In this paper, we use a hierarchy template model to fit/reconstruct point clouds without the processes of noise removal or sharp feature detection. In particular, the complicated process such as parameterization or correspondence establishment is not required. The only one thing is to select a proper template model to fit point clouds. The template model is formed by the defined primitive geometrics including plane, sphere, and cylinder. In the fitting process, we directly solve a least-square linear system instead of a non-linear one. This makes our approach be efficient and robust in modeling point clouds.

The remainder of this paper is organized as follows. Section 2 reviews the related works on point cloud modeling. Algorithm overview is described in Section 3. Our methods are introduced in Section 4. Section 5 shows the experimental results with discussion. Conclusions and future works are given in Section 6.

II. RELATED WORK

We classify the previous works about point cloud fitting into three categories, *implicit-based*, *topology-based*, and *template-based*, based on what kind of surface representation is used in fitting. In the topology-based category, many approaches have been proposed including the ball-pivoting algorithm [12] and Delaunay-based algorithms [11,18-20]. They handle the point cloud modeling problem from a computational geometry viewpoint. They address on the topology problem and let the constructed surfaces exactly pass the sampled points. Thus, these approaches are intrinsically sensitive to noises. This makes them infeasible to handle point clouds captured from digital scanners.

An alternative approach is to reconstruct a smooth implicit surface that approximate the point clouds, i.e., the implicit-based category [2-10,21,22]. Interpolating a set of points with radial basis functions (RBF) [5,9], a signed distance function [21] or locally fitted implicit quadrics (MPU) [6], or modeling using moving least-square (MLS) technique [2-4,22] offers a smooth 3D object representation. However, as mentioned in Section 1, the sharp features are also smoothed in the approximation. This would lead to failure in feature detection.

In the template-based category, many approaches have been proposed to fill missing parts of incomplete point cloud model by utilizing the geometry information of the template model [13-17]. They establish a mapping between the point and template models for accurately filling the holes. In [17], the authors present an example-based completion framework. The template models are retrieved from a database. They treat surface completion as a case of mesh merging. The retrieved templates are warped to align the point model, and then blended together to fill holes. In [13], similar to [17], an incomplete target model is merged with a selected template model. To establish the correspondence between the template and target models, they embed them onto a base mesh. This approach is very robust even for an incomplete model containing large complex holes or multiple components. The approach presented in [14] directly deforms the template model to approximate the incomplete point model. In this paper, instead of completing holes, we focus on the accuracy modeling of noisy point cloud captured from airborne-based or ground-based digital scanning system. By directly solving a least-square linear system, we can fit a template model to a point clouds.

III. SYSTEM OVERVIEW

Fig.1 illustration the workflow of proposed modeling algorithm. Given a set of unorganized points, in the preprocessing, we segment point cloud into several primitive geometric groups (Fig. 1(a)) (there are three types of geometrics: plane, cylinder and sphere). Next, each point group is approximated by its related primitive geometry (Fig. 1(b)). Here, a direct least-square fitting approach is adopted. By incorporating these fitted primitive geometrics with some geometry constraints defined in the template, we solve a least-square linear system again (Fig. 1(d)) for the purpose of increasing modeling accuracy.

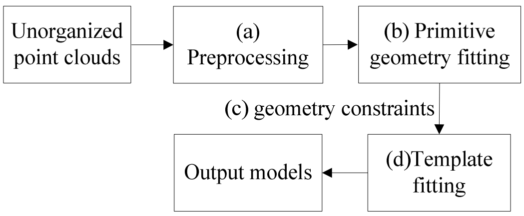


Fig. 1 System workflow.

IV. TEMPLATE-BASED POINT CLOUD FITTING

A. The algebra of primitive geometry

Point clouds sampled from city buildings (captured from airborne-based or ground-based scanning system) generally contain a lot of sharp edges and corners. Therefore, it is suitable to select the primitive geometries, plane, sphere, and cylinder, for data fitting. The approaches of fitting these three types of geometries are not novel now. Many approaches have been proposed in the past. They can be classified into geometric approach [24] and algebraic approach [23]. In geometric approaches, they minimize the sum of the squared Euclidean distances to the given point cloud. The geometric fitting has several drawbacks. First, the problem is formulated as a non-linear system. Thus, the linearization process is required and the solution can only be found using an iterative and expensive process. An elegant alternative approach is to substitute the geometric distance by an algebraic distance [23]. In this way, the fitting can be archived by directly solve a least-square linear system. Here, we first describe the algebras of primitive geometrics, plane, sphere, and cylinder, in Eqs. (1)-(3), respectively.

$$f(x_i, y_i, z_i) = Ax_i + By_i + Cz_i + D = 0, \tag{1}$$

where (A, B, C) represents the plane normal.

$$f(x_i, y_i, z_i) = A(x_i^2 + y_i^2 + z_i^2) + Dx_i + Ey_i + Fz_i + G = 0, \tag{2}$$

subject to $D^2 + E^2 + F^2 - 4AG < 0$,

$$\begin{aligned} f(x_i, y_i, z_i) = {} & Ax_i^2 + By_i^2 + Cz_i^2 + Dx_i + Ey_i + Fz_i \\ & + Gx_i y_i + Hy_i z_i + Ix_i z_i + J = 0 \end{aligned} \tag{3}$$

B. Direct least-square fitting of algebra template

The least-square fitting process for sphere is described only. As for other primitive geometries, the readers can derive by the same process. Given a set of points $\{(x_i, y_i, z_i)\}_{i=1}^N$ containing N points, we want to find a sphere, represented by the coefficient A, D, E, F, G (see Eq. (2)), which approximates these points. The fitting of a sphere to a set of points can be approached by minimizing the sum of squared algebraic distances of the points to the sphere. The algebraic distance of point (x_i, y_i, z_i) to the sphere is formulated in Eq. (4).

$$\min_a \sum_{i=1}^{N} f(x_i, y_i, z_i)^2 = \min_a \sum_{i=}^{N} (x_i \cdot a)^2 \tag{4}$$

where $x = [x^2 + y^2 + z^2, x, y, z, 1]$ and $a = [A, D, E, F, G]^T$.

The problem of Eq. (4) can be solved directly by a standard least squares approach, but the fitting result can be an ellipsoid or sphere. To ensure the solution is a sphere, the appropriate constraint Eq. (5) is added to Eq. (4).

$$D^2 + E^2 + F^2 - 4AG = 1 \tag{5}$$

By rewriting the above constraint in matrix form, the Eqs. (4) and (5) can be reformulated as :

$$\min_a \| \mathrm{D}a \|^2 \quad \text{subject to } a^T \mathrm{C} a = 1 \tag{6}$$

where the design matrix D and constraint matrix C is:

$$\mathrm{D} = \begin{bmatrix} x_1^2 + y_1^2 + z_1^2 & x_1 & y_1 & z_1 & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_i^2 + y_i^2 + z_i^2 & x_i & y_i & z_i & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_N^2 + y_N^2 + z_N^2 & x_N & y_N & z_N & 1 \end{bmatrix}$$

$$\mathrm{C} = \begin{bmatrix} 0 & 0 & 0 & 0 & -2 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ -2 & 0 & 0 & 0 & 0 \end{bmatrix}$$

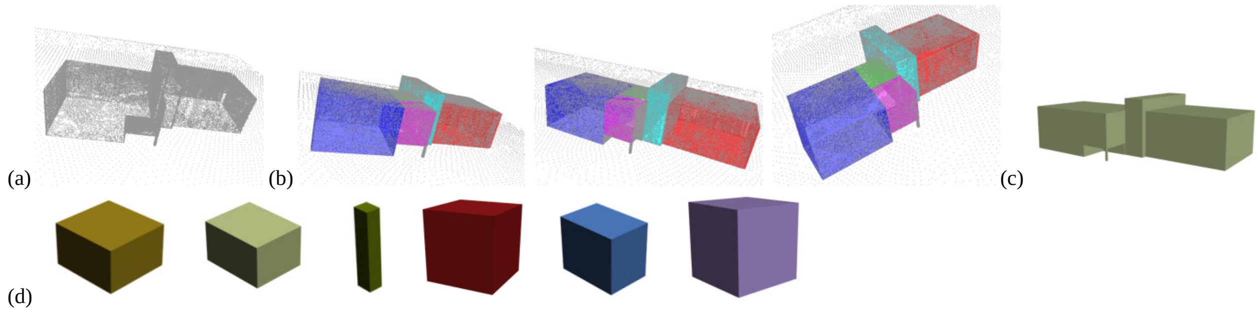


Fig. 5 The point cloud reconstruction result. (a) The source point clouds; (b) the visualization of the primitive geometries fitting (the primitive geometries are visualized in different colors); (c) the reconstruction result; (d) the primitive geometries.

The solution a of this minimization problem yields as the eigenvector the smallest positive eigenvalue of the following generalized eigen-problem:

$$D^T Da = \lambda Ca \tag{7}$$

To increase the modeling accuracy, we integrate all geometric algebras of template models and add some geometric constraints in the least-square linear system. For install, two planes $P_1 = [A_1, B_1, C_1, D_1]$ and $P_2 = [A_2, B_2, C_2, D_2]$ are perpendicular to one another. Thus, we set $(A_1, B_1, C_1) \cdot (A_2, B_2, C_2) = 0$ as soft constraint in the linear system. We show an example of hierarchy template in Fig2. In this case, there are three levels in the template model. In the first level, there are two boxes (formed by twelve planes), two cylinders and one plane. In the second level, the two boxes and two cylinders are combined to form two simple shapes, respectively. In the third level, these two simple shapes are combined with a plane to form the final template model. Using this template to fit the point cloud (Fig. 2 Left) can obtain a fitting result (Fig. 2 Right).

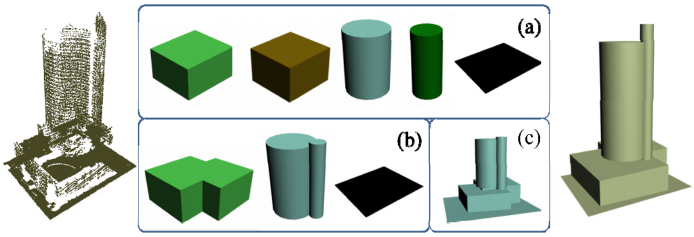


Fig. 2 Left: the source point cloud; Middle: (a) the level-1 primitive geometries; (b) the level-2 shapes; (c) the final template model; Right: the fitting results.

V. EXPERIMENTAL RESULTS

To demonstrate the robustness and feasibility of the proposed point cloud modeling approach, both articulated (Figs. 5 and 6) and real data (Fig. 3) were experimentally evaluated. The proposed method is based on the hierarchy algebraic template. Therefore, we start this section with the visualization of the decomposed primitive geometrics and their fitting results (shown in Figs. 3 and 5-6). Obviously, the primitive geometries are decomposed and fitted well in these two experiments. In Fig. 4 and Table 1, we show the comparison between point cloud modeling with and without geometric constraints. The results show the modeling accuracy is increased by integrating geometric constraints in least-square fitting. In Fig. 7 and Table 1, we also show the comparison between our approach and Poisson approach [7]. We can see that surface reconstructed by Poisson approach still contains significant noises, and misses thin and small surface.

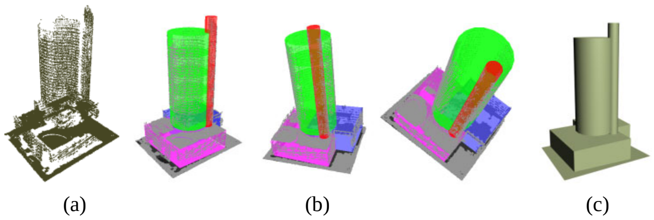


Fig. 3 The reconstruction result (a) The input point cloud; (b) the primitive geometries (displayed in different colors); (c) the reconstruction result.

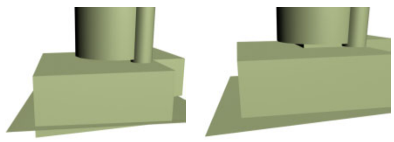


Fig. 4 A comparison between construction without (Left) and with (Right) geometric constraints.

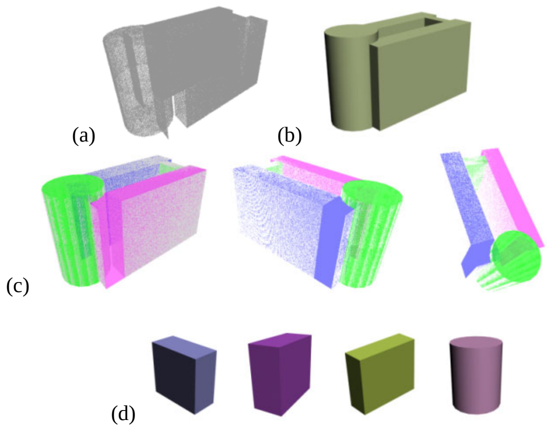
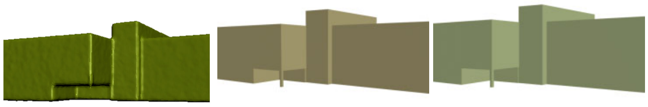


Fig. 6 The point cloud reconstruction result. (a) The source point clouds; (b) the visualization of the primitive geometries fitting (the

primitive geometries are visualized in different colors); (c) the reconstruction result; (d) the primitive geometries.



(a) (b) (c)

Fig. 7 A comparison of point cloud reconstruction. (a) The Poisson approach [7]; (b) our approach without any geometry constraint; (c) our approach with geometry constraint.

Data	#V.	Approaches	Reconstruction Error RMS	PSNR
Fig. 5	107,914	(a)	0.513	43.045
		(b)	0.744	39.888
		(c)	0.512	43.102
Fig. 6	177,945	(a)	0.832	38.170
		(b)	0.639	40.643
		(c)	0.569	41.474

Table. 1 A statistics. 1st row: the test point clouds; 2nd row: the number of points (#V.); 3rd row: the approaches ((a): the Poisson approach [7]; (b): our approach without any geometry constraints; (c) our approach with geometry constraints); 4th row: the reconstruction error (the error is measured by root mean square (RMS) and peak signal-to-noise ratio (PSNR)).

VI. Conclusions

We presented a novel template-based building modeling technique for 3D point clouds. Based on direct least-square fitting, a hierarchy algebraic template with user-defined geometric constraints are used to approximate the point clouds contains only simple geometries such as plane, sphere, and cylinder. The experimental results show that our approach can deal with noisy point clouds containing sharp features. This make the propose approach feasible to be applied in cyber city modeling.

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References

[1] S. Fleishman, D. Cohen-Or, and C. T. Sliva, “Robust moving least-squares fitting with sharp features”, Proceedings of ACM SIGGRAPH 2005, pp. 544-552.
[2] M. Alexa, J. Behr, D. Cohen-Or, S. Fleishman, D. Levin, and C. T. Silva, “Point Set Surfaces”, In IEEE Visualization 2001, pp. 21-28.
[3] N. Amenta, and Y. J. Kil, “Defining point-set surfaces”, Proceedings of ACM SIGGRAPH 2004, pp. 264-270.
[4] D. Levin “Mesh-independent surface interpolation”, In Geometric Modeling for Scientific Visualization, pp. 37-49, 2003.
[5] J. C. Carr, R. K. Beatson, J. B. Cherrie, T. J. Mitchell, W. R. Fright, B. C. McCallum, and T. R. Evans, "Reconstruction and representation of 3D objects with radial basis functions" , Proceedings of ACM SIGGRAPH 2001, pp. 67-76.
[6] Y. Ohtake, and A. Belyaev, M. Alexa, G. Turk, and H.-P. Seidel, "Multi-level partition of unity implicits", Proceedings of ACM SIGGRAPH 2003, pp. 463-470.
[7] M. Kazhdan, M. Bolitho, and H. Hoppe, "Poisson surface reconstruction", Symposium on Geometry Processing, pp.61-70, 2006.
[8] X. Wu, M. Yu, and Q. X. Wang, "Implicit Fitting and Smoothing Using Radial Basis Functions with Partition of Unity", Computer Aided Design and Computer Graphics, 9th International Conference on, pp. 139-148, 2005.
[9] B. S. Morse, T. S. Yoo, P. Rheingans, D. T. Chen, and K. R. Subramanian, “Interpolating implicit surfaces from scattered surface data using compactly supported radial basis functions”, Shape Modeling International, pp. 89-98, 2001.
[10] G. Guennebaud, and M. Gross, "Algebraic point set surfaces", Proceedings of ACM SIGGRAPH 2007, pp. 23.1-23.9.
[11] N. Amenta, M. Bern, and M. Kamvysselis, “A new voronoi-based surface reconstruction algorithm”, Proceedings of ACM SIGGRAPH 1998, pp. 415–422.
[12] F. Bernardini, J. Mittleman, H. Rushmeier, C. Silva, and G. Taubin, “The ball-pivoting algorithm for surface reconstruction”, IEEE Transactions on Visualization and Computer Graphics, Vol. 5, No. 4, pp. 349-359, 1999.
[13] V. Kraevoy, and A. Sheffer “Template Based Mesh Completion”, In Eurographics Symposium on Geometry Processing, pp.13-22, 2005.
[14] C. Stoll, Z. Karni, C. Rössl, H. Yamauchi, and H.-P. Seidel, “Template Deformation for Point Cloud Fitting”, Eurographics Symposium on Point-Based Graphics, pp. 27-35, 2006.
[15] B. Allen, B. Curless, and Z. Popovic, “Articulated Body Deformation from Range Scan Data”, ACM Transactions on Graphics, Vol. 21, No. 3, pp. 612-619, 2002.
[16] K.-S. Cheng, D., Wang, W., Qin, H., Wong, K.-Y. Yang, K., H., and Liu, Y.: Fitting Subdivision Surfaces to Unorganized Point Data Using SDM, Pacific Conference on Computer Graphics and Applications, pp. 16-24, 2004.
[17] M. Pauly, N. J. Mitra, J. Giesen, M. Gross, and L. Guibas, “Example-based 3D Scan Completion”, Symposium on Geometry Processing, pp.23-32, 2005.
[18] C. C. Kuo, and H. T. Yau: A Delaunay-based region-growing approach to surface reconstruction from unorganized points. Computer-Aided Design, vol. 37, pp. 825-835, 2005.
[19] C. C. Kuo, and H.T. Yau: A New Combinatorial Approach to Surface Reconstruction with Sharp Features. IEEE Trans. Vis. Comput. Graph., pp. 73-82. 2006.
[20] N. Amenta, and M. Bern, “Surface reconstruction by Voronoi filtering”, Discrete and Computational Geometry. Vol. 22, pp. 481-504, 1999.
[21] H. Hoppe, T. DeRose, T. Duchamp, J. McDonald, and W. Stuetzle “Surface reconstruction from unorganized points”, ACM SIGGRAPH’92, pp. 71-78, 1992.
[22] S. Fleishman, D. Cohen-Or, and C. T. Silva, “Robust moving least-squares fitting with sharp features”, ACM. Transactions on Graphics, 24(3):544–552, 2005.
[23] V. Pratt., “Direct least-squares fitting of algebraic surfaces”, Computer Graphics, 21(4):145–151, July 1987.
[24] W. Gander, G. H. Golub, and R. Strebel, “Leastsquares fitting of circles and ellipses”, BIT Numerical Mathematics, Vol.3, No. 4, pp. 558–578, 1994.