方向性情報を持っていない三次元点群からの表面形状の復元

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1. Introduction

Surface reconstruction is a critical stage in the 3D data acquisition and model creation system. Most existing reconstruction algorithms are designed for oriented data, i.e. point sets with surface normals. Despite the advance of modern 3D scanning technology, under certain circumstances, orientation information may not be available or reliable, e.g. specular reflections, material artifacts, shadowing. Besides, the noise or defects, e.g. holes or non-uniform sampling, contained in the point sets challenge the reconstruction algorithms to faithfully recovery the shape of 3D models. We present a robust method that achieves smooth surface approximation from unoriented and defective point sets by *orientation inference* and *volumetric regularization.*

2. Proposed Method

The proposed method takes a local approximation strategy while also aims to achieve noise suppression by volumetric regularization [1]. The proposed method is comprised of two main stages: *orientation inference* of a set of unoriented local surfaces and *model repairing*. In the first stage, surface approximation is driven by adaptive octree subdivision which partitions the input point set P into a number of local point sets P_i of low complexity, where i is the index of octree cells. The local surfaces f_i represented by radial basis functions (RBFs) are then fitted by solving a linear system with P_i treated as constraints. Specifically, some *off-surface constraints* created by projecting P_i along the normals of the best-fitted planes corresponding to P_i are also required in RBF fitting. It is worth noting that the local surfaces thus fitted are not consistently oriented

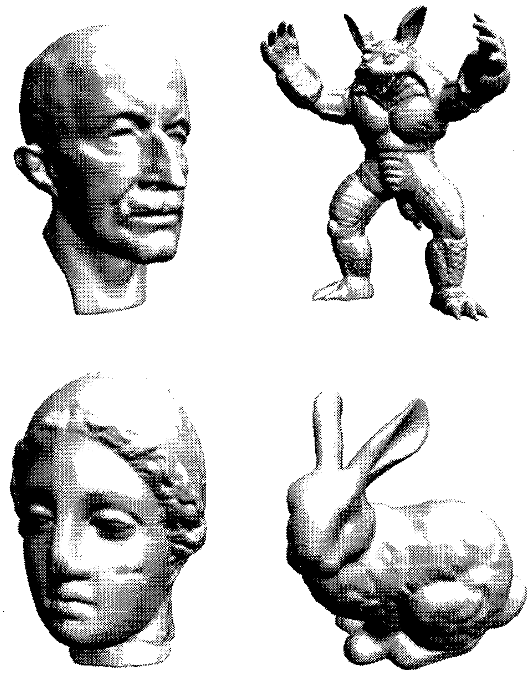

Figure 1. Several reconstructed models by the proposed method.

because the off-surface constraints are not created by real surface normals. We apply a new orientation inference algorithm to obtain the globally consistent orientation of all the local surfaces with respect to the full model. Orientation inference is a binary optimization process which assigns each f_i a label $l_i \in \{-1, 1\}$ in a way such that f_i is consistently signed with the overall implicit surface. In essence, neighboring f_i are treated as nodes and linked together to form a graph. An energy function is defined on the graph so as to penalize the inconsistent orientation change between nodes. The optimal label assignment is obtained by minimizing the total energy by belief propagation or graph cuts algorithms. One advantage of the proposed method is that to determine the orientation of *continuously* defined functions rather than *discretely* sampled points is potentially more robust against non-uniformly distributed data points and abrupt orientation change. For example, the

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surface normals of neighboring points around sharp features are very likely to be mis-aligned while an implicit function fitted to a sharp feature is easier to be orientated. In the second stage, we utilize the observation that surface normals vary smoothly in most regions of a 3D model to perform model repairing. The orientation consistency of neighboring f_i is checked to measure their *vulnerability* by evaluating the gradient directions. It is worth noting that it is not feasible for the previous methods [2] to perform similar vulnerability checks because these orientation propagation algorithms align the unoriented normal directions based on the same assumption. The f_i of high vulnerability are typically erroneously fitted implicit surfaces. For robust model fitting, we evaluate the reliable f_i to obtain an estimate of surface normals within their support regions. The vulnerable f_i are then iteratively refitted by enlarging their support regions to include more oriented points as constraints. Since most RBF centers are repeated, we apply the *Schur Complement formula* [4] to efficiently update the RBF coefficients by using partial results of previous iteration.

Table 1. Computational times represented in seconds.

Model	Num of points	Octree Subdivision	Local Fitting	Orientation
Bunny	35947	1.16	6.45	8.13
RockerArm	40177	0.625	4.32	4.54
MaxPlanck	49132	0.79	6.94	5.92
Venus	134345	0.89	19.86	8.89
Armadillo	172974	4.02	21.78	23.38

3. Experimental Results

We have applied the proposed method to reconstruct implicit surfaces from several real-world scanned data sets, as shown in Figure 1. The computational times are summarized in Table 1. Generally, the proposed method is efficient and the whole reconstruction process can be finished in a few seconds. To evaluate the effectiveness of orientation inference, we have compared the proposed method with the *orientation propagation* method proposed in [2]. The point set used in Figure 2 was obtained from an image-based reconstruction method and is qualitatively inferior in terms of noise, non-uniformity and holes. We used the previous method to perform surface estimation and orientation alignment. The orientated point cloud was then passed to the Poisson reconstruction algorithm [3] to generate an implicit surface (Figure 2, bottom). Because of the defects contained in the point cloud, the previous method mis-aligned some of the surface normal vectors, which resulted in erroneously reconstructed surface. In contrast, the proposed method successfully reconstructed the implicit surface from the defective point set without any artifacts (Figure 2, upper).

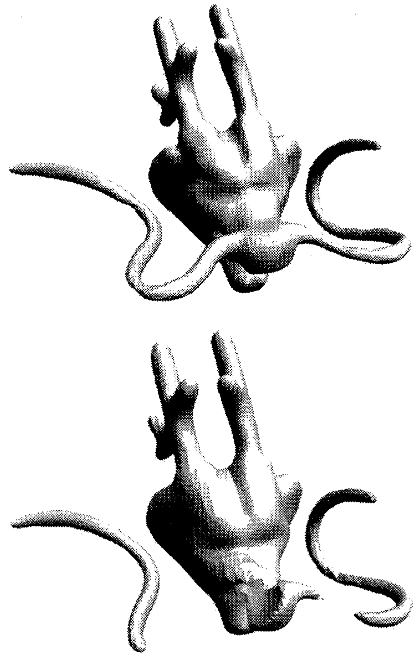

Figure 2. Poisson reconstruction [3] by using the oriented point clouds obtained from our method (upper) and [2] (bottom).

References

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