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PHOTO-CONSISTENT SURFACE RECONSTRUCTION FROM NOISY POINT CLOUDS

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ABSTRACT

Existing algorithms for surface reconstruction from point sets are defeated by moderate amounts of noise and outliers, which makes them unapplicable to point clouds originating from multi-view image data. In this paper, we present a novel method which incorporates the input images in the surface reconstruction process for a better accuracy and robustness. Our approach is based on the medial axis transform of the scene, which our algorithm estimates through a global photo-consistency optimization by simulated annealing. A faithful polyhedral representation of the scene is then obtained by inversion of the medial axis transform.

Index Terms— Surface reconstruction, point cloud, medial axis transform, stereovision.

1. INTRODUCTION

The problem of approximating a surface from a set of sample points has received a considerable interest in computational geometry, and more generally in mesh processing and in computer graphics. This problem, which is referred to as surface reconstruction, arises in many applications of science and engineering. Many approaches have been proposed [1, 2, 3], among which some offer theoretical guarantees on the output geometry and topology when the input sampling is sufficiently dense. Of particular interest in this work is the Power Crust algorithm [2], which builds a discrete approximation of the medial axis transform, then recovers a polyhedral surface as its inverse.

However, all the aforementioned algorithms assume that the sample is free of noise and outliers. This is an important restriction, since no real scanning device provides exact data. To handle this problem, some recent algorithms have been developed. In [4] theoretical guarantees have been provided by considering a noise model in which both the sampling density and the noise level depend on the local level of surface detail. A limitation of their algorithm is that it does not handle arbitrarily over-sampled datasets. This limitation has been overcome in a recent paper [5]. This work augments the Power Crust algorithm [2] with a greedy filtering process which discards parts of the medial axis transform originating from noise. However, the noise assumptions used in these two recent works do not hold in practice: the density and the noise level of samples produced by real scanning devices do not depend on the local feature size of the surface.

In this paper, we tackle the special case of point clouds extracted from calibrated multi-view image datasets. These point clouds typically feature higher levels of noise and higher proportions of outliers than those of active scanning devices. This discards most, if not all, standard surface reconstruction algorithms. Our work continues along the line of [5, 2]: it replaces the greedy estimation of the medial axis transform with a global photo-consistency optimization by simulated annealing, thus yielding improved accuracy and robustness.

The remainder of this paper is organized as follows. Section 2 presents some useful computational geometry concepts. Our method is described in Section 3 and is experimentally validated in Section 4.

2. BACKGROUND

2.1. Medial axis transform

Since its introduction by Blum [6], the medial axis (and the skeleton, a closely related mathematical notion), has become a standard tool in shape analysis, recognition and classification. Formal definitions vary from author to author. Please refer to a recent review [7] for a thorough mathematical presentation.

Here, we define the medial axis of a closed bounded surface \( S \) as the closure of the set of points with at least two closest points on \( S \), among which some offer theoretical guarantees on the output geometry and topology when the input sampling is sufficiently dense. Of particular interest in this work is the Power Crust algorithm [2], which builds a discrete approximation of the medial axis transform, then recovers a polyhedral surface as its inverse.

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2.2. Voronoi diagram, poles, polar balls

We now consider the transposition of the above continuous notions to the discrete case. Of particular interest in surface reconstruction is the result by Amenta and Bern [1] that, given a sufficiently dense sample P = {p₁, . . . , pₙ} ∈ ℝ³ of a surface S, the medial axis of S is approximated by a subset of the Voronoi diagram of P.

We recall that the Voronoi cell of a point pᵢ, denoted by V(pᵢ), is the region of space that is closer from pᵢ than from all other points in P:

\[ V(pᵢ) = \{ x ∈ ℝ³ : ∀ j, \| x - pᵢ \| ≤ \| x - pⱼ \| \}. \]

V(pᵢ) is a convex polytope, possibly unbounded. The Voronoi diagram of P is roughly the set of cells, convex polygonal facets, edges and vertices induced by the Voronoi cells V(pᵢ). For illustration purposes, Figure 1(b) shows the Voronoi diagram of a set of points in the plane.

Following [1], we call poles the vertices of the Voronoi diagram that approximate the medial axis. A pole is called an inner pole or an outer pole depending on whether it lies inside or outside S. We call polar ball a maximal ball centered at a pole whose interior does not intersect P. In other words, the radius of a polar ball is the distance from the pole to its closest points in P. Figure 1(c) shows the set of inner and outer polar balls of the Voronoi diagram 1(b).

The set of all inner and outer polar balls is the discrete counterpart of the medial axis transform. Similarly to the medial axis transform, the set of polar balls can be inverted: the Power Crust algorithm [2] builds a polyhedral surface that approximates the input point set P, by computing the power diagram of the set of polar balls.

2.3. Power diagram and power crust

We denote by bᵦ₋,ρ a ball of radius ρ centered at c. The power distance between two balls bᵦ₋,p₁ and bᵦ₋,p₂ is defined by

\[ d_{\text{pow}}(bᵦ₋,p₁, bᵦ₋,p₂) = \| c₁ - c₂ \|^2 - \rho₁^2 - \rho₂^2. \]

Using this distance, we can generalize the Voronoi diagram of a set of points to a set of balls B = {bᵦ₋,p₁, . . . , bᵦ₋,pₙ}: the power cell of a ball bᵦ₋,pᵢ is the region of space where a non-weighted point x is closer from bᵦ₋,pᵢ, in term of power distance, than from all other balls in B. The different power cells induce the power diagram. Like Voronoi diagrams, power diagrams have convex polytope cells. Figure 1(d) shows the power diagram cells of the inner and outer polar balls in Figure 1(c).

Consider the polar balls of a point sample P of a surface S. The power crust is the boundary between the power cells of inner polar balls and the power cells of outer polar balls. It is a polyhedral surface which approximates the surface under some sampling assumptions [2].

2.4. Surface reconstruction

We now focus on the problem of surface reconstruction: S is unknown. P may not fulfill the aforementioned sampling assumptions, and is corrupted by a certain amount of noise and outliers. The previous notions are then faced to significant difficulties: (i) the classification of poles as inner or outer is no more straightforward, (ii) due to noise and outliers, some poles may not approximate the medial axis.

In the original Power Crust algorithm [2], poles are labeled as inner or outer by a greedy propagation process driven by a priority queue. Unfortunately, this greedy approach has been shown to fail with a moderate amount of noise and outliers in [8].

3. APPROACH

In this work we propose to replace the greedy estimation of the medial axis transform with a global photo-consistency optimization by simulated annealing. A faithful polyhedral representation of the scene is then obtained by inversion of the medial axis transform.

3.1. Formulation

Given a sample set P = {p₁, . . . , pₙ} ∈ ℝ³, we denote by B = {b₁, . . . , bₘ} the set of m polar balls of the corresponding Voronoi diagram. We define \( \tilde{l} = \{ l₁, \ldots , lₘ \} \in \{-1, 0, +1\}^m \) a labeling vector describing the state of the
When a predefined time limit is over. The algorithm returns the optimal labeling vector 

\[ \vec{l} \]

obtained by \[11\] and we have reduced the optimization space by considering noise levels of the dataset. The optimization process is initialized with a labeling vector \( \vec{l}_0 \) and we have compared our method with a recent multi-view reconstruction method \[11\]. We have validated our method on real datasets publicly available at \( http://www.cgal.org/ \)[10]. We have compared our method with a recent multi-view reconstruction method \[11\] robust to outliers. Our experiment uses the eight views Herz-Jesu-P8 dataset from \[12\]. Some images of this dataset are shown in Figure 3(c). 6950 points are generated by matching image keypoints. In order to reduce the computation time of our method we have initialized it with a labeling vector obtained by \[11\] and we have reduced the optimization space to the set of polar balls with radius smaller than the characteristic noise level of the dataset. The optimization process terminated after 40 minutes on a standard workstation. Two other methods have also been tested as sanity checks: the reconstruction algorithm \[5\] and the Laplacian smoothing algorithm which have been both initialized by the result of \[11\]. We have compared the cumulative error distribution of the four meshes with respect to the mesh obtained by the LIDAR technique provided by \[12\]. Table 1 shows the error distribution of the results provided by an automatic multi-view evaluation program \[12\]. For each method four cumulative error distributions have been computed. Column \( n \sigma \) represents the percentage of image pixels with an error less than \( n \sigma \), where \( \sigma \) is the characteristic noise of LIDAR. More accurate results yield to higher scores in the table. Figure 2 shows the meshes obtained by four experimented methods. Our result compares favorably with the three other methods in terms of accuracy and robustness. In a second experiment we have initialized a variational multi-view stereovision method \[13\] with our mesh and with the output of \[11\]. Figures 3(a) and 3(b) show the results obtained by the two initializations. The results show that \[13\] provides more accurate and less noisy surface when it is initialized by our method.

### 3.2. Optimization

In order to minimize \( 1 \), we use the simulated annealing optimization algorithm \[9\]. The algorithm starts with an initial labeling vector \( \vec{l}_0 \). A global variable \( T \) is taken as the temperature of the optimization process, it is initialized to \( T_0 \). At each iteration, it takes a random pole \( b_i \) in \( B \). Then, it changes its label \( l_i \) to a random new state and computes the energy variation \( \delta E \). If \( \delta E \) is negative, it accepts the new labeling and goes to next iteration. Otherwise, it decides with a probability given by a function \( Pr(\delta E, T) \) if the new state should be accepted. In case it should not, it returns to the old configuration. The temperature \( T \) decreases during the process by a function which depends on the number of passed iterations. The algorithm stops when the energy is sufficiently low, or when a predefined time limit is over. The algorithm returns \( S_{B}(\vec{l}) \) as the final surface.

### 4. EXPERIMENTAL RESULTS

We have tested our method on a real dataset publicly available at \( http://cvlab.epfl.ch/~strecha/multiview/ \). All implementations have been done using CGAL library (\( http://www.cgal.org/ \))[10]. We have compared our method with a recent multi-view reconstruction method \[11\] robust to outliers. Our experiment uses the eight views Herz-Jesu-P8 dataset from \[12\]. Some images of this dataset are shown in Figure 3(c). 6950 points are generated by matching image keypoints. In order to reduce the computation time of our method we have initialized it with a labeling vector obtained by \[11\] and we have reduced the optimization space to the set of polar balls with radius smaller than the characteristic noise level of the dataset. The optimization process terminated after 40 minutes on a standard workstation. Two other methods have also been tested as sanity checks: the reconstruction algorithm \[5\] and the Laplacian smoothing algorithm which have been both initialized by the result of \[11\]. We have compared the cumulative error distribution of the four meshes with respect to the mesh obtained by the LIDAR technique provided by \[12\]. Table 1 shows the error distribution of the results provided by an automatic multi-view evaluation program \[12\]. For each method four cumulative error distributions have been computed. Column \( n \sigma \) represents the percentage of image pixels with an error less than \( n \sigma \), where \( \sigma \) is the characteristic noise of LIDAR. More accurate results yield to higher scores in the table. Figure 2 shows the meshes obtained by four experimented methods. Our result compares favorably with the three other methods in terms of accuracy and robustness. In a second experiment we have initialized a variational multi-view stereovision method \[13\] with our mesh and with the output of \[11\]. Figures 3(a) and 3(b) show the results obtained by the two initializations. The results show that \[13\] provides more accurate and less noisy surface when it is initialized by our method.

### 5. DISCUSSION AND CONCLUSION

We have proposed a photo-consistent surface reconstruction method from noisy point clouds based on the estimation of the medial axis transform. Our work replaces the greedy algorithms of \[5, 2\] with a global photo-consistency optimization by simulated annealing. We have validated our method on real datasets. Our results compare favorably with state of
the art methods in terms of accuracy and robustness to noise. A drawback of our method is its computational complexity due to the optimization process. We hope that by modifying the form of the energy function we will be able to use more practical optimization algorithms such as graph-cuts.

6. REFERENCES


