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RECONSTRUCTION OF SURFACE FOR IMAGE PROCESSING

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ABSTRACT

In this paper we are going to use a physically motivated method for surface reconstruction that can recover smooth surfaces from noisy and sparse data sets. No orientation information is required. By a new technique based on regularized-membrane potentials the input sample points are aggregated, leading to improved noise tolerability and outlier removal, without sacrificing much with respect to detail (feature) recovery. In this method, sample points are first aggregated on a volumetric grid. A labeling algorithm that relies on intrinsic properties of the smooth scalar field which emerging after the aggregation, is used to classify grid points as exterior or interior to the surface. We also introduce a mesh-smoothing paradigm based on a mass-spring system, enhanced with a bending-energy minimizing term to ensure that the final triangulated surface is smoother than piecewise linear. The method compares favorably with respect to previous approaches in terms of speed and flexibility.

KEYWORD: Mass-spring system, membrane potential, point cloud, regularization, surface reconstruction, volumetricsegmentation.

INTRODUCTION

The goal of surface reconstruction is to obtain a digital representation of a real, physical object or phenomenon described by a cloud of points, sampled on or near its surface. In this paper, we propose a novel technique for surface reconstruction, which employs regularized-membrane potentials, evaluated on a volumetric grid, to output smooth surfaces from noisy and sparse data. The purpose of these potentials is twofold: to aggregate data points and to remove outliers due to noise. In the following we denote by aggregation the process in which gaps between the data points are bridged by a slowly-varying scalar field.

The purpose of surface reconstruction is to obtain a digital representation of a real, physical object or phenomenon described by a cloud of points, which are sampled on or near the object's surface. The growing interest in this field is due to the increasing availability of point-cloud data, such as may be obtained from medical scanners, laser scanners, vision techniques (e.g., range images), and other modalities. In computer vision, shape recovery is a classical problem, whose goal is to derive a 3-D scene description (e.g., surface normal and surface depth) from one or more 2-D images. All techniques that recover shape are commonly called "shape-from-X," where X can be shading, stereo, texture, or silhouettes, etc. (see [1]–[5] and the references therein). For example, in the stereo problem, one first extracts features (e.g., corners, lines, etc.) from a collection of input images, and then solves the so-called correspondence problem, i.e., matching features across images. After obtaining depth information at the locations of the extracted features, one needs to reconstruct the surfaces of the objects present in the scene. One way of achieving this is by using techniques that reconstruct surfaces from point clouds.

PROPOSED ALGORITHM

Fig. 1 shows the computational flow diagram of our method. First, the input sample points (assumed to be without any orientation information) are assigned to grid cells, using cloud-in-cell (CIC) interpolation (first step in Fig.1) Perform aggregation of the sample points by computing regularized membrane potentials on the grid. A labeling algorithm, which follows increasing paths of the scalar field (starting from the bounding box and marching towards the data points), is used to classify the grid points into exterior and interior to the surface, thus defining an implicit (rough) surface. Prior to polygonization, we again use diffusion potentials, but this time with the purpose of producing a smooth implicit surface. Then, we employ Bloomenthal's polygonizer[14] to turn the implicit surface into a triangulated one , and use a mass-spring system, enhanced with a bending-energy minimizing term, in order to obtain a larger degree of surface smoothness.

MODULE:

The work can be divided into four models-
Module 1: Aggregation of input data points.
Module 2: Classification of grid cells.
Module 3: Surface smoothing and polygonisation.

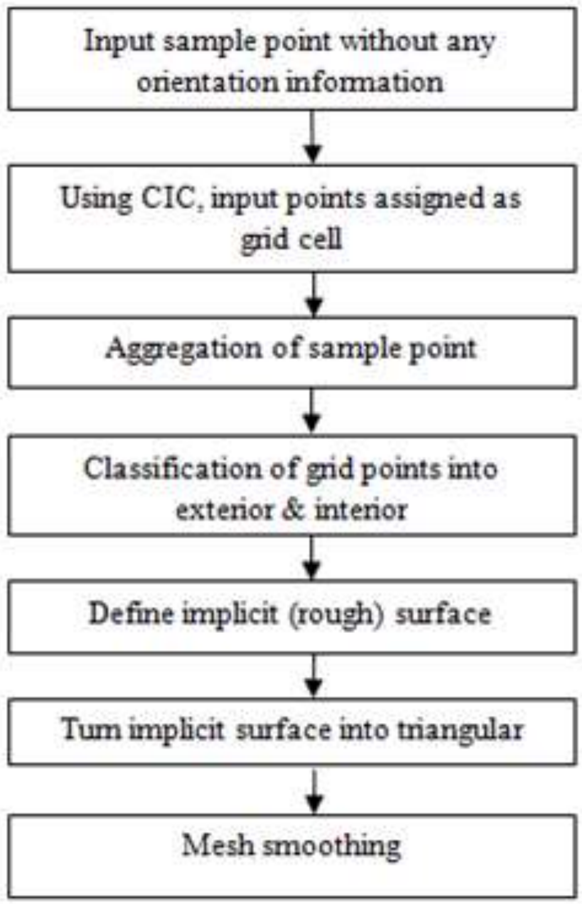


Fig.1. flow diagram of the proposed method

MODULE DESCRIPTION:

The first step assigns the input data points to cells of a 3-D grid using the CIC interpolation scheme. Then aggregation of the sample points is performed by computing regularized-membrane potentials on the grid labeling algorithm, which follows increasing paths of the scalar field, is used to classify the grid points into exterior and interior to the surface, thus defining an implicit (rough) surface. Prior to polygonisation, diffusion potentials is again used, but this time with the purpose of producing a smooth implicit surface. Then Bloomenthal's polygonizer[14] is employed to turn the implicit surface into a triangulated one and use a mass-spring system, enhanced with a bending-energy minimizing term, in order to obtain a larger degree of surface smoothness.

MODULE 1:

This step assigns the input data points to cells of a 3-D grid, using the CIC interpolation scheme. Accordingly, a constant numerical value (we fix this value to one), representing the contribution of each data point to the initial (heat) distribution, is spread to the eight nearest cell centers. The weights are given by the overlap volumes of a box, centered around the data point under consideration, with the neighboring voxels. If several points contribute to the same cell, the values are accumulated. The nonempty grid cells will serve as sources generating potentials on the grid. The nonempty grid cells, called source points, are regarded as sources for the physical simulation of heat flow, as defined by the linear diffusion equation.

Aggregation has the disadvantage that it converges to a constant steady state. That is, the size of the support regions around the cells corresponding to the input points increase with the number of iterations, so that the diffusion would eventually converge to a constant solution covering the whole volume. Two heat sources are placed at positions and from the temporal evaluation of the pure diffusion process, one can easily notice that after the positions of the two maxima (corresponding to the sources) can barely be distinguished.

Since we are not interested in the steady state of linear diffusion, a criterion is required for choosing a stopping time. This can be done with the help of an additional reaction term. This keeps the steady state close to the initial value, leading to the regularized membrane equation.

MODULE 2:

After aggregation, a method is needed which separates the exterior grid points from the interior ones, thus defining the primary implicit surface. This method should start from the bounding box of the computational grid, follow increasing paths of the scalar field on the grid towards the source points, and label grid cells as exterior, as it proceeds. After the propagation has stopped at regional maxima and ridges, the boundary separating the remaining (interior) points from the exterior points can be traced to yield the reconstructed surface. This process is repeated until the maximum distance of the temporary boundary points is smaller than some preset distance threshold.

Our algorithm starts also by labeling all points as interior. Then, the points situated on the bounding box of the grid are inserted in a queue (enqueued) and assigned some temporary value, TRIAL. Then, the subspace is swept as follows. Each trial point is removed from the queue (dequeued) and checked to see if it has at least an interior neighbor that has a smaller value of the potential scalar field. Only if it does not have such a neighbor, the point is turned into an exterior point and all its interior neighbors are inserted into the queue, as trial points. Otherwise, none of its neighbors is enqueued and its label remains untouched. This case, in which the marching front reaches an interior point with a smaller value, may occur in two situations: (i) either the front has just arrived at the true location of the boundary separating surface interior from exterior, or (ii) the point has a neighbor which has been labeled beforehand. In the first case, the algorithm should stop turning interior neighboring points into exterior points, since these points are situated on the other side of the advancing front, and they are truly interior points.

About point cloud:

A point cloud is a set of vertices in a three-dimensional coordinate system. These vertices are usually defined by X, Y and Z coordinates. Point clouds are most often created by 3D scanners. These devices measure a large number of points on the surface of an object, and output a point cloud as a data file. The point cloud represents the visible surface of the object that has been scanned or digitized. Point clouds are used for many purposes, including creating 3D CAD models for manufactured parts, metrology/quality inspection, and a multitude of visualization, animation, rendering and mass customization applications.

Convex hull:

In mathematics, the convex hull or convex envelope for a set of points X in a real vector space V is the minimal convex set containing X. In computational geometry, it is common to use the term "convex hull" for the boundary of the minimal convex set containing a given non-empty finite set of points in the plane. Unless the points are collinear, the convex hull in this sense is a simple closed polygonal chain.

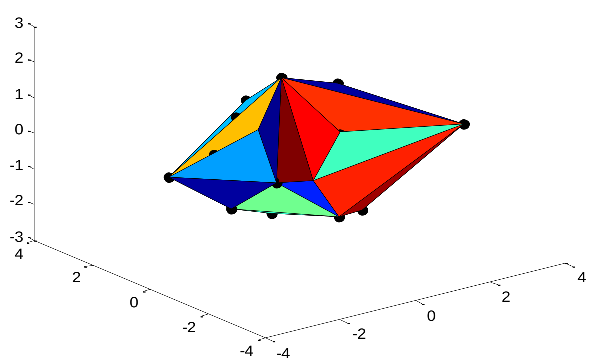
About Voxels:
A voxel (volumetric pixel) is a volume element, representing a value on a regular grid in three dimensional spaces. This is analogous to a pixel, which represents 2D image data in a bitmap (which is sometimes referred to as a pixmap). As with pixels in a bitmap, voxels themselves do not typically have their position (their coordinates) explicitly encoded along with their values.

MODULE 3:
It undergo steps like
Interpolation Using Membrane Potentials:
Direct polygonisation will cause "staircase" artifacts in the resulting mesh. A better approach is to interpolate the implicit surface using the reaction-diffusion process a second time, with the labeled grid points as sources. Sources are instantiated only at the locations of the interior and exterior grid points since the membership of boundary points is uncertain. By tracing the zero iso-contour a smooth scalar field emerges and the implicit surface is turned into a triangulated one. Since boundary voxels form thin bands along surface borders, a small number of iterations is required, resulting in fast computation. The triangulated surface, which is a better approximation to the real surface than the initial one, is used as initialization for the more computationally demanding mass-spring system.

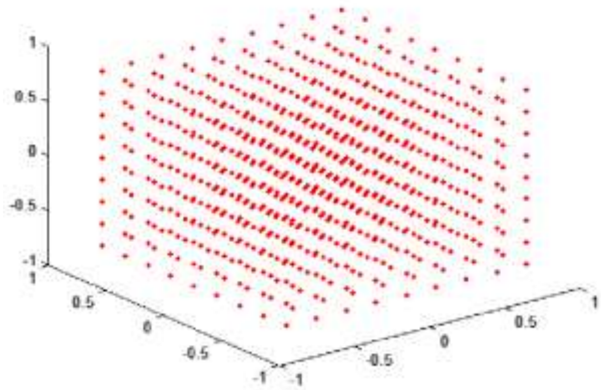
Mesh Smoothing With a Mass-Spring System:
Assuming that the correct topology has been inferred and the triangulated surface possesses consistent orientation we propose a mass-spring system for obtaining a larger degree of smoothing. That is, each edge of each triangular patch comprising the mesh is modeled by a spring and each vertex is regarded as a particle with a small mass. Since we utilize triangular elements, we do not need to include extra cross springs to afford resistance against shearing. In addition, we integrate an extra energy term such that the bending energy of the system is minimized. This has the beneficial effect, analogous to curvature flow, that the triangulated surface is smoothened by moving its vertices along their normals with a speed proportional to the (normal) curvature.

EXPERIMENT AND RESULT
Matlab 7.0 software platform is use to perform the experiment. The PC for experiment is equipped with an Intel P4 2.4GHz Personal laptop and 2GB memory.
From experiment results, we can draw to the conclusion that we have introduced a novel framework for surface reconstruction starting from unorganized point clouds without orientation information.

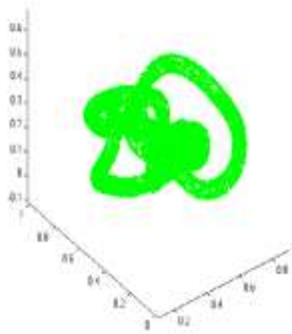
CONVEX HULL RESULTS



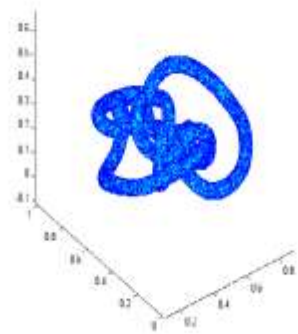
POINT CLOUD



Final Out put :



Points Cloud



Output Surface

The difference between points cloud & output surface is that, in cloud based extraction we can see only the structural part but not able to see what is happing on the surface. The main advantage of the work is that, we are able to clearly see the structural part as well as what is happing on the surface.

CONCLUSION

We have introduced a novel framework for surface reconstruction starting from unorganized point clouds without orientation information, and demonstrated its effectiveness in various experimental settings. The method can be used to efficiently reconstruct surfaces from clean as well as noisy data sets, and in our opinion, this represents an advantage over existing methods. For example laughing Buda, any normal damage been happen on the image surface will be clearly viewed.

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