Title:
Functional Surface Reconstruction from Unorganized Noisy Point Clouds

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Introduction:
Nowadays, it becomes easily to obtain large and complex object models composed of point clouds sampled from real-world objects with the help of high precision 3D scanners. As a result, point-based techniques such as point rendering, parameterization, simplification, shape reconstruction become hot research topics in Computer Aided Design, Computer Graphics and Reverse Engineering. So far, considerable works have been done to reconstruct surfaces from the point clouds. The main goal of this work is also to develop a new method for curved surface reconstruction directly from unorganized noisy point clouds, especially for functional surface reconstruction.

Methods regarding the surface reconstruction from the unstructured point clouds have been proposed, such as Delaunay tetrahedralization, the level set method, radial basis function (RBF) and compactly supported radial basis function (CSRBF) [1,2]. However, Delaunay tetrahedralization based methods may fail when dealing with noisy point clouds. The level set method is proved powerful for surface reconstruction but its implementation is expensive in time and memory when high accuracy reconstruction is required. Although implicit surface reconstruction methods are attractive, finding a set of functions to form an implicit surface is difficult, especially for the free form surface. As a result, surface reconstruction from noisy point clouds is still an open question, let alone reconstructing the surface with regard to its function.

Main idea:
In this paper, a new procedure for functional surface reconstruction directly from unorganized point clouds is introduced. The input to our algorithm is unorganized noisy point clouds captured from different functional surfaces (Fig. 1(a)). A multi-scale operator via computing the difference of normals (DoN) is applied to the input for obtaining boundaries of functional surfaces (Fig. 1(b)). Points are then clustered according to the surface they associate by a simple algorithm (Fig.1.(c)) and each cluster reconstructs a functional surface (Fig.1(d)).

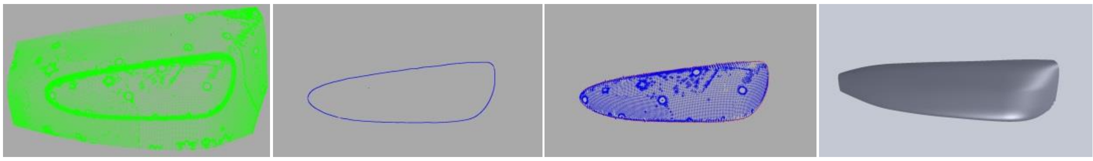

Fig. 1: Proposed method: (a) Input noisy point clouds, (b) Detected boundary of a functional surface by DoN, (c) Points corresponding to the same functional surface, and (d) Reconstructed functional surface.

Boundary points detection

Given a point cloud $P = \{p_i \in R^3\}$, where $i = 1,2,\cdots,m$ and m indicates the number of points, the normal *n(p)* at each point $p \in P$ is often estimated ahead of any point processing technique. When *n(p)* is evaluated, some neighbors $N \subseteq P$ of p are always involved. And a common way to define N is by $N = \{q \in P | dis(p,q) < r\}$, where r indicates a user defined radius and *dis()* represents the Euclidean distance. The estimated normal $\check{n}(p)$ at p may be affected by N, which depends on the location of p. By using this fact, a multi-scale operator by calculating DoN was first proposed in [3] and applied to point cloud segmentation. The operator is given as

$$n_d^1(p, r_1, r_2) = |\check{n}(p, r_1) - \check{n}(p, r_2)| \tag{2.1}$$

where $r_1, r_2 \in R$ signify the radii and $\check{n}(p, r)$ presents the estimated normal at p with radius r.

However, it is difficult to find the points locating on peaks or valleys with Equ. 2.1. To solve this problem, a variant of DoN is given here

$$n_d^2(p, r) = \max |\check{n}(p, r, N_i) - \check{n}(p, r, N_j)| \tag{2.2}$$

where $i, j = 1,2,\cdots g, i \neq j, N_i \subset N(p), N_j \subset N(p), N_i \cap N_j = \emptyset, \sum_{k=1}^{k=g} N_k = N(p)$ and g is a user defined threshold.

Combining the above two operators, we get an extended difference of normals operators.

$$n_d(p, r_s, r_l) = \alpha n_d^1(p, r_s, r_l) + \beta \max(n_d^2(p, r_s), n_d^2(p, r_l)) \tag{2.3}$$

where α and β are two user defined coefficients and $0 \leq \alpha \leq 1$, $0 \leq \beta \leq 1$, $\alpha + \beta = 1$.

With the above operator, we can easily get the boundary points B of a functional surface as that shown in Fig.1(b).

Point clouds clustering

After obtaining the boundary points B of a functional surface, we cluster the input points according to B. This is achieved by the following algorithm.

Algorithm 1 : Points clustering

Input:
  $V := P - B$, $c := \frac{\sum_{p \in B} p}{\#\{p \in B\}}$
  $R = \{\}$
Do:
  while V is not empty **do**
    x:=pop(V)
    y:=argmin$_{p \in B}$ $dis(x, p)$
    if $\vec{xy} \cdot \vec{xc} < 0$ & $dis(y, c) > dis(x, c)$ **then**
      $R := R \cup \{x\}$
    end if
  end while
Output:
  R

After grouping the input points according to the functional surface as shown in Fig.1(c) we need to use them to reconstruct the functional surface.

Functional surface reconstruction

With R we reconstruct the corresponding functional surface by fitting. To get an editable surface, we fit a NURBS surface to R and finally we get the desired functional surface as shown in Fig. 1(d).

<u>Conclusions:</u>

In this paper, a new procedure for functional surface reconstruction directly from an unorganized point cloud is proposed. First, a multi-scale operator by computing the difference of normals is used to detect the boundary points of functional surface. Then the points corresponding to the same functional surface are grouped and used to reconstruct the curved functional surface. Although the feasibility of the proposed method is proved by experimental results, modifications and improvements should be made in the future to make the proposed method more robust and efficient.

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