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Technical Section

A statistical approach for extraction of feature lines from point clouds ☆

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ABSTRACT

This paper firstly introduces the use of a statistical model based on the Poisson distribution as a tool for extracting feature points from point clouds. When the features on a model are non-uniform or the surfaces are not completely smooth, the thresholds for different local features must be set differently. Such case is ill-suited to all previous global fixed thresholds dependent methods. The Poisson distribution based method is preferable because it computes different thresholds for different local features adaptively depending on the natural properties of the surfaces. Secondly, the region information analysis is employed to cluster the border/edge points, identify the corner points and acquire the link information for feature lines. Finally, the complete feature lines are reconstructed based on the geometry representations of the border point clusters that are created by adapting L_1-median locally, instead of using distance/path parameters. The proposed method does not need any prior surface reconstruction and is not largely affected by noisy points, neighborhood scales or sampling quality. We demonstrate the benefits of our method with the favorable results for real-world point clouds with varying types of features and the application of the generated feature lines to the computer aided line-drawings generation of Terracotta.

1. Introduction

Digital scanner technology is an active data acquisition technology which provides an efficient solution to acquire high-resolution surfaces of real-world objects. Consequently, geometric processing of point clouds is becoming increasingly important. In a lot of applications, the input data is typically a large point set acquired by 3D scanning devices. Thus feature detection on point cloud is attractive as it can be used to support most preprocessing steps.

In point clouds, the surface of a 3D object is described by a set of sample points without further topological information such as triangle mesh connectivity or a parameterization. The feature lines on a surface which facilitate a better understanding of the surface can be used in a variety of applications [1], e.g. computer vision, scientific computing, medical imaging, shape recognition and computer aided design. It would thus be useful to know the points belonging to features.

Conventionally, feature lines extraction can be solved in two stages: feature points detection and feature lines reconstruction. In the first stage, feature detection is a challenging task that classifies points into two opposite classes depending on certain thresholds: feature points versus non-feature points. The previous threshold-dependent methods have two common defects: setting global fixed thresholds, which requires the model to be completely smooth, or the features are uniform, or else only very sharp features are extracted; and setting different thresholds for different models, which requires continuous user interaction with the model. As users may have little advance knowledge of the model, either of these makes feature extraction for point clouds very energy-wasting.

In the second stage, the extracted feature points are scatter points which do not have any cluster information or link information. Thus, the two main methods creating feature lines are both based on the distance/path parameters which take no consideration of the whole geometries of the feature point clusters. So they may result in inaccurate segments of feature lines and the errors may accumulate in subsequent steps.

To alleviate this, the present paper proposed a statistical approach to extract feature lines directly from a given point cloud.

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The feature lines here are defined as the border of the different surface patches, which can serve as an input for many processing applications, such as meshing, models segmentation or geometric reconstruction. First, to extract feature points, we focus specifically on a statistical approach, which is based on the Poisson distribution. This approach can solve the problems described above because it allows us to compute different thresholds for different local features adaptively but to set the same threshold for different models. Second, in order to reconstruct the feature lines, it creates geometry representations for feature point clusters by adapting L_1-medians locally and then complete the feature lines depending on link information, instead of using distance/path parameters directly to create feature lines.

Our main contributions are:

- A statistical approach based on Poisson distribution goes beyond user-setting feature measures of previous feature extraction methods.
- Adapting L_1-medians locally enables line reconstruction based on the geometry of feature points and link information.

The main benefits of our method are:

- The proposed method computes different feature measure thresholds for different local features adaptively.
- The results do not depend on the significance of the features.
- The proposed method does not need any prior surface reconstruction and is not largely affected by noisy points, neighborhood scales or sampling quality.
- Feature lines are reconstructed depending on link information and the geometries of the feature point clusters instead of using distance/path parameters.

2. Related works

A variety of methods have investigated the extraction of features on meshes, such as [2–5]. The underlying connectivity information and normals associated with the vertices of the mesh make it more convenient to extract features from meshes. A problem of point based methods is the lack of any normal and connectivity information of the model. This makes feature detection a more challenging task than in mesh based methods. However, mesh reconstruction based approach may work [6], but the sharp features of the original model are often smoothed-out in triangle meshes, and moreover, the success of features extraction depends on the ability of the polygonal meshing procedure to accurately build the sharp edges [7]. Furthermore, the construction of a mesh is non-trivial, computationally expensive, and sometimes it can be hard to generate a mesh. Our aim is however to work directly on the point cloud not with meshes.

Gumhold et al. [8] use Riemannian tree to build the connectivity information and then use covariance analysis to compute a probability of a point belonging to what kind of features. Pauly et al. [9] present a related method but extend it with a multi-scaling analysis of the neighborhoods to get more information. Ho et al. [10] and Park et al. [11] also present a multiscaling analysis method, which respectively use curvedness and tensor voting strategy to determine whether a point is a feature point. Miltiscaling analysis methods enhance the robustness of an algorithm but increase the computational cost as well. These four methods use local feature detection operators but global fixed thresholds to extract feature points.

Daniels et al. [7] present a robust feature extraction method that leverages the concept of RMLS (Robust Moving Least Squares) to locally fit surfaces to potential features. Merigot et al. [12] use a so-called Voronoi covariance measure to estimate principle curvatures and normal directions of the underlying surface from a given point cloud, which can be applied to feature detection in point cloud data by iteratively computing covariance matrices with varying neighborhoods. These two methods are based on the observation that features are near potential feature lines.

Related to the above two methods, the following two methods are based on the observation that features are near intersection between the potential piecewise smooth surfaces. Demarsin et al. [13] use segmentation to search for closed sharp features in point clouds based on normal estimation and region growing method. Jenke et al. [14] also propose a feature detection method based on region growing strategy, which uses probability to decide whether a point is a feature point. However, this method uses curvature information that is difficult to estimate in a noisy environment and is not robust to fade-out feature lines. Weber et al. [15] concentrate on sharp features too. They first compute a Gauss map clustering on local neighborhoods in order to discard all points which are unlikely to belong to a sharp feature. The remaining features candidates then undergo a more precise iterative selection process.

For feature lines reconstruction, there are two main methods. Refs. [8] and [9] both use a minimal spanning tree to achieve the feature lines. Similar to this method, Ref. [13] uses point clusters in the minimum spanning tree instead of vertices. Both the two related methods need some optimizing processes such as adding edges, pruning branches, cutting cycles and closing the feature lines, all of which use the path parameter in the graph as the discipline. Ref. [7] implements a smoothing filter on the feature points and then approximate the thin feature points a smooth curve by ordering and linking the points based on the PCA (Principle Component Analysis) strategy. Similarly, the ordering-linking method also uses the distance parameter to select the appropriate points from the candidates and link them directly to create the feature polylines, as well as gap completion and corner creation.

There are some other methods extracting line segments directly [16,17], which are used in some specific datasets, for example, the urban scene.

Feature lines can be defined as the border of the various surface patches [13] which can be extracted by segmenting the given 3D model into different surfaces. Multiple techniques have researched the surface segmentation of 3D models, which are grouped into three main categories: edge-based [18], face-based [19,20] and clustering-based [21]. Face-based techniques are the mostly similar to ours, which usually work by searching out points belonging to the same surface, with edges being derived by intersection or other computations from the surface patches. However, most of these methods are not robust to fade-out feature lines.

The Poisson distribution was originally used to analyze rates of conviction in France during the 1820s [22], and is now a common research application in a variety of fields, such as Poisson-based regression models [23].

The concept of L_1-median has long been known in statistics [24,25]. Recently, L_1-median has been successfully applied to point cloud processing. Lipman et al. [26] introduce a locally optimal projection operator based on L_1-median for surface approximation from point clouds. Huang et al. [27] introduce L_1-median skeleton as a curve skeleton representation for 3D point clouds.

3. Overview

This section provides an overview (as shown in Fig. 1) of our approach which contains three main stages:

1. *Feature extraction*: The input is an unorganized point cloud $P=\{p_j\}_{j\subset J}\in R^3$ which may exhibit varying degrees of noise and