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Extracting feature lines from point clouds based on smooth shrink and iterative thinning

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ABSTRACT

An index of measuring the variation on a surface called the smooth shrink index (SSI) which presents robustness to noise and non-uniform sampling is developed in this work. Afterwards, a new algorithm used for extracting the feature lines was proposed. Firstly, the points with an absolute value of SSI greater than a given threshold are selected as potential feature points. Then, the SSI is applied as the growth condition to conduct region segmentation of the potential feature points. Finally, a bilateral filter algorithm is employed to obtain the final feature points by thinning the potential feature points iteratively. While thinning the potential feature points, the tendency of the feature lines is acquired using principle component analysis (PCA) to restrict the drift direction of the potential feature points, so as to prevent the shrink in the endpoints of the feature lines and breaking of the feature lines induced by non-uniform sampling.

1. Introduction

The extraction of feature lines, as a basic operation in geometric model processing, can provide important information for the expression and understanding of 3-d models. Therefore, it has been widely applied in the visualisation [1], optimisation [2,3], and simplification [4–6] of geometric models, surface reconstruction [7], smoothing surfaces [8,9], and so on.

A feature line is the ordered connection of the feature points. Therefore, the primary step when extracting a feature line is to seek an index used for measuring the degree of variation of the surface to identify potential feature points from the whole point cloud. For this purpose, the principle component analysis(PCA) [10–13], curvature method [14–21] and M estimation [22–24] were proposed. However, the measurement of the surface variation of scattered point clouds has to be further discussed due to the lost topology, non-uniform sampling, and noise interference. Also, identified potential feature points require to be processed by the curve growing algorithm or the minimum spanning tree (MST), so as to obtain orderly connected feature lines. In this process, problems such as breakage and bifurcation of the feature lines induced by noise and non-uniform sampling must to be taken into account.

A new algorithm that can extract feature lines from the non-uniformly sampled point cloud containing noise is proposed in this research. Firstly, a new index, that is, the SSI for measuring the degree of variation of the surface is constructed based on the smooth shrinkage of the model, and then used to identify potential feature points from the whole point cloud. Afterwards, the growing algorithm is used to conduct regional segmentation of the potential feature points. Finally, the potential feature points of each region are subjected to independent iterative refinement using the bilateral filter algorithm based on curvature and distance. The feature points are then connected to form the feature lines. The main contributions in this paper are as follows: (1) a new index SSI for measuring the degree of variation of the surface is proposed. Due to its integral characteristics, SSI has favourable tolerance to noise. Meanwhile, by weighting the sampling density and restraining the shrinkage direction, SSI shows favourable adaptability to non- uniformly sampled point clouds. In addition, SSI is capable of expressing the concavity and convexity of the surface by calculating the angle between the shrink direction and the normal vector. (2) A method for identifying potential feature points that are subordinate to different feature lines is proposed. This method improves the distinction of ridge and valley lines by considering the spatial distance and the concavity and convexity of the surface while conducting regional segmentation on the potential feature points. Meanwhile, after regional segmentation, a greater radius of neighbourhood can be adopted to determine trends in curves, which is favourable for improving the stability while thinning the potential feature points later on. (3) Existing methods for thinning the potential feature points have been improved. While thinning the potential feature points, PCA is used to determine the curve direction and restrain the drift of potential feature points. In this way,

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problems such as breakage and the shrink in the endpoints of feature lines that frequently appear in traditional methods can be avoided.

The rest of the paper is arranged as follows: Section 2 reviews related work; the proposed SSI is introduced in Section 3; Section 4 describes the algorithm for extracting feature lines and its implementation; Section 5 verifies the proposed algorithm and compares it with other algorithms; and a summary of this research is presented in Section 6.

2. Related work

It is difficult to extract feature lines from scattered point clouds without connected topology. Many algorithms are proposed to solve this problem. Generally speaking, the entire process of extraction of feature lines can be divided into two parts: the identification of the potential feature points, and their connection.

2.1. Identification of potential feature points

Gumhold et al. [10] first introduced PCA for the extraction of feature lines: they used the eigenvalues obtained from PCA to construct an index named Surface Variation (SV), so as to identify the potential feature points. Then, the eigenvector from PCA is used to divide the potential feature points into the boundary points, edge points, and corners. Finally, the MST of the feature points is established to connect the feature points. By extending the aforementioned method, Pauly et al. [12,13] carried out multi-scale PCA on a point cloud by changing the number of neighbourhood points, which improves the adaptability of the algorithm to noisy point clouds. By using SV instead of the curvature, the aforementioned feature measurements can preferably represent the bending degree of the surface. However, SV can merely reflect the bending amplitude of the surface, but cannot represent the concavity and convexity, according to its positive or negative sign, just like that of the actual curvature. Therefore, the aforementioned methods cannot distinguish the spatially adjacent valley and ridge lines correctly.

To obtain the curvature of the point cloud according to the standard definition, surface fitting was introduced. Wang et al. [14] proposed an algorithm for extracting feature lines from the point cloud based on local reconstruction. This algorithm searches for the feature points by judging the number of surfaces to which a potential feature point is subordinate, and can preserve weak feature lines as much as possible while extracting significant features lines. However, this algorithm merely performs simple plane fitting for neighbourhood points, and thus is not applicable to the extraction of the feature lines generated by intersected bending surfaces. Pang et al. [15] calculated the curvature by fitting a local quadratic surface, and then acquired the strengthened feature points by projecting feature points onto the nearest potential feature lines. Although this method can extract both smooth and fine features, it is likely to give rise to a loss of information and the breakage of the extracted feature lines because the feature points require to be projected on the tangent plane for processing. The moving least-squares algorithm was used by Kim et al. [16–17] and Weber et al. [18] to estimate the curvature information of the point cloud. Kim acquired the neighbourhood information by calculating the local Voronoi map, and similar methods were also adopted by Quentin *et al* [19]. However, a Voronoi map is likely to be affected by any outliers. Daniels et al. [20] fitted surface using robust moving least-squares analysis, and then projected the potential feature points onto the intersecting lines of different surfaces to obtain the feature lines. As the moving least-squares surface is applied as a tool for curvature estimation in the aforementioned methods, these methods are endowed with limited speed of operation. Therefore, their use is slow when processing point clouds with large data sets and have poor processing effect on non-uniformly sampled point clouds. The fast Fourier transform was adopted to calculate the curvature of the point cloud by Enkhbayar *et al* [21]. Although, this method can be accelerated by parallel calculation, it has to establish local coordinate systems for each point in the point cloud using PCA and conducts the projection calculation in advance. These steps are time-consuming, and satisfying results cannot be obtained until the calculated results are filtered through a low pass filter.

Since measurement noise is inevitable in practical point clouds, methods based on statistical analysis were proposed to eliminate the influence of noise with large amplitude. Evangelos et al. [22] greatly improved the accuracy when estimating the curvature of noisy, non-uniformly sampled point cloud data using M estimation, but the time complexity is high. The multi-scale tensor voting was used by Min et al. [23] to calculate the degree of variation of the surface, which presents high efficiency and better adaptability to noise, but poor adaptability to non-uniformly sampled point clouds. Weber et al. [24] realised the extraction of the feature lines by clustering the Gauss maps of neighbourhood points. This algorithm exhibits favourable robustness, but cannot extract smooth feature lines because it is designed to extract sharp feature lines.

2.2. The connection of the feature points

The connection of the feature points needs the potential feature points, so as to form orderly, connected feature lines. The line growing method is one of the methods used to connect feature points. For example, Enkhbayar et al. [21] firstly thinned the identified feature points, from which a seed point was found. Then, they added other feature points based on the seed point and the curve tendency to generate the integral feature lines. Kim et al. [17] used the Voronoi map to construct the connected topology, and realise the growth of the feature curve by taking the curvature direction into account. As another connection method, the integral method usually realises the connection of feature points by constructing the MST of the potential feature points. For instance, Pauly et al. [12] firstly established the undirected connection map for the potential feature points, and then calculated the weights of each side of the connection map based on the degree of variation of the surface and the distance to construct the MST. Finally, the orderly connected feature lines were generated after the short sides were removed. Demarsin et al. [11] firstly used the normal vector to conduct regional segmentation over the whole point cloud, and then constructed the MST for the boundary points of the region to extract the closed feature line. MST was used by Gerhard et al. [25] to construct the minimum spanning graph for the boundary points, from which the closed boundary lines were extracted.

3. Smooth shrink index (SSI)

Since feature lines are usually located in the place where the surface varies most significantly, a measurement index is therefore required to represent the degree of variation in the surface. In light of the processing requirements for practical scanning point clouds, this measurement index is supposed to be robust enough to noise and non-uniform sampling.

According to the definition, curvature directly reflects the variation of a surface. As for scattered point cloud data, the local point cloud data are required to be parameterised before fitting the parametric surface (quadratic or spline). Then, the curvature at the calculation point of the parametric surface is applied as the calculation result. Although, the curvature method shows favourable effects on the point cloud not containing noise, it exhibits lower precision to the practical scanning point cloud as it has to use the