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Feature-aware filtering for point-set surface denoising

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ABSTRACT

In this paper, we propose a simple and effective feature-aware filtering for point-set surface denoising, which can achieve a second-order surface approximation of the underlying surface. Our method consists of two stages: robust normal estimation considering sharp features and feature-preserving denoising using a local curvature based projection. The normal clustering based on neighborhood grouping allows the filter to preserve and respect several features during the denoising process. We demonstrate the strength of our method in terms of denoising, feature preservation and computational efficiency.

1. Introduction

Recently, in spite of remarkable progress of the 3D scanning technology, a measurement dataset is still contaminated by random noise, due to surface reflection, sensing error or misalignment of partial scans. Therefore, denoising of a raw point-dataset is a vital task for preprocessing before subsequent geometry processing, mesh generation and visualization.

Since Hoppe et al. [1] introduced the surface reconstruction framework, many researchers have paid attention to restoring a surface from imperfect point sets over the past two decades [2–4]. Various surface reconstruction methods for noisy point clouds originated from using moving least squares (MLS) approximation of data [5–7]. Furthermore, the edge-sharpening algorithm on coarse meshes has been introduced to restore a sharp feature in the presence of aliasing artifacts produced by feature-insensitive sampling [8,9].

In this paper, we aim to cleanup the noisy point-set surfaces that possibly contain various salient features with tangent discontinuities. Previous denoising filters [10], projection operators [11] and geometric diffusions [12] usually work well on the corrupted data, but sharp features might be blurred undesirably in the presence of extreme severe noise. They depend on local surface approximations or averaging normal over the neighborhood, resulting in a wrong normal field of point-sets or undesired denoising results for several features.

The main purpose of this paper is to develop a robust and fast feature-preserving filter of a point-set surface (Fig. 1). The key idea is to detect sharp features and to compute multiple normal clusters at tangent discontinuity points via a consistent neighborhood grouping based on the tensor voting theory [13]. The proposed denoising filter uses the normal fields of points as the local curvature estimates. We use a non-iterative two-step process. First, we perform the tensor voting for every point to label sharp features, and compute point normals separately at the feature and non-feature points. Then, the second-order filtering is applied to the noisy dataset. The new position of a point is found by minimizing the distance to the second-order predictor defined by a local curvature. The outline of our method is given in Fig. 2.

The robust normal estimates are crucial in our filtering. Thus, we organize a consistent neighborhood, called *the adaptive sub-neighborhood*, that includes points only belonging to the same structure, and then approximate the local tangent plane using the sub-neighborhood. The proposed method prevents sharp feature details from smoothing and better recovers the underlying geometry in the curved regions than the first-order filtering. Here are the main contributions of this paper:

1. We achieve perceptual grouping for a consistent neighborhood via tensor voting. This treats points on the opposite surface across a sharp feature as outliers, and thus makes normal estimation and filtering more robust in the presence of sharp features.
2. We propose a novel second-order filtering based on point normals and curvatures. It is very simple and effective since no time-consuming optimization process is required to define local second-order predictors.

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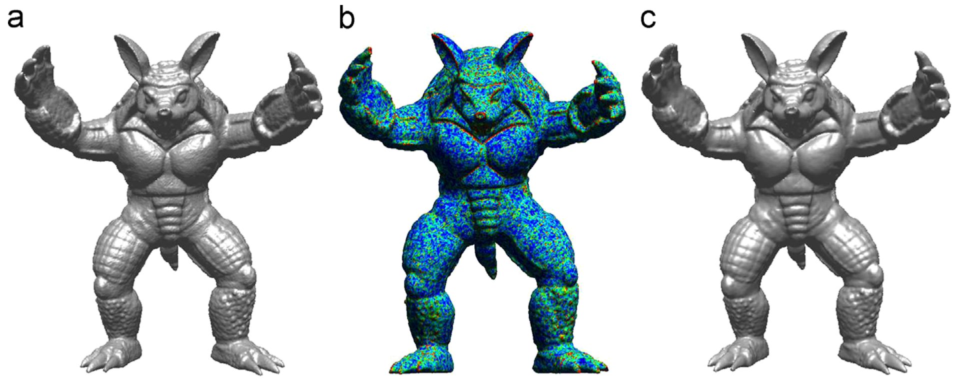

Fig. 1. (a) The Armadillo model with the synthetic noise, (b) the color-coded feature distribution extracted from the noisy surface, and (c) the denoised surface using our filter. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this article.)

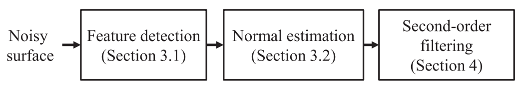

Fig. 2. Outline of the proposed method.

2. Related work

Denoising raw point sets is a fundamental problem for pre-processing in 3D surface modeling and a variety of studies on this issue have been conducted based on differential geometry and signal processing. The earliest work on surface denoising and fairing is the Laplacian smoothing. Taubin [14] developed a surface fairing algorithm by defining the discrete Laplacian of a surface by weighted averages over the neighborhoods. Desbrun et al. [15] introduced the curvature-based geometric diffusion of irregular meshes to remove rough features, and improved the computational efficiency and stability by an implicit integration of the diffusion equation. Both methods worked only for a mesh, but they motivated the research on point-set surface denoising.

Pauly et al. [16] defined the discrete Laplacian at a point using a simple umbrella operator and proposed the smoothing filter by applying it to the diffusion equation in [15]. But this method cannot preserve some geometric details or salient features. Since then, many studies have mostly focused on feature-preserving smoothing of a 3D surface. Fleishman et al. [10] and Jones et al. [17] commonly extended the bilateral filtering [18] to a feature-preserving surface smoothing tool. In [10], the heights of vertices over the local tangent plane are regarded as the grayscale intensity values of an image, and the height value obtained by the bilateral filtering over the neighborhood becomes a new offset of each vertex. Then, the point is updated along the normal direction by the offset. Jones et al. [17] presented a non-iterative feature-preserving filtering technique with two steps consisting of normal mollification and position update based on the predictions from the spatially nearby triangles. Thereafter, Jones et al. [19] proposed the normal filtering for smooth point rendering using a spatial deformation. Only normals are refined for natural visualization. Duguet et al. [20] extended the bilateral filtering in [17] to second-order filtering based on the surface curvature by jet estimation for point cloud data. This technique can smooth the noisy point data or perform the feature enhancement in high curvature regions, while failure cases can occur in sharp creases with tangent discontinuities.

Clarenz [21,22] presented a framework for fairing point-based surface via finite element based partial differential equations. Lange and Polthier [12] also presented an anisotropic Laplacian smoothing of a point-set surface using the curvature information. But their methods also cannot deal with the degeneracy on the tangent discontinuities of models.

Recently, the notion of non-local means [23] is applied to 3D point-set filtering in [24]. These techniques may result in a better performance and outcome at times, while an assumption that self-similarities exist in the model should be met.

All the above denoising techniques do not preserve sharp features and surface details, or require a considerable time to obtain fine filtering results. In contrast, our filter preserves discontinuities faithfully and is also much simpler than previous second-order filtering methods.

3. Normal estimation

The first phase in our pipeline is to perform robust normal estimation. The key idea is to maintain the multiple normals at tangent discontinuity points, rather than one averaging vector. To this end, sample points are classified into either a sharp feature or a non-feature. Then, we compute the point normals separately at the feature and non-feature points using our sub-neighborhood set. In this section, a fast and robust method is presented for sharp feature detection and normal computation.

3.1. Sharp feature detection for a point-set surface

Tensor voting is a robust framework for perceptual organization and structure inference. It was applied to the dimensionality estimation [25] and sharp feature extraction in point clouds [26,27]. We also apply this scheme for neighborhood grouping and sharp feature detection; computing the normal voting tensor and analyzing its basis.

The local tangent space can be approximated by the outer product of a unit vector $\hat{\mathbf{v}} = (\mathbf{q}-\mathbf{p})/\|\mathbf{q}-\mathbf{p}\|$ connecting two points $\mathbf{p}$ and $\mathbf{q}$. The normal space among a point and its neighborhood is simply computed by subtracting the tangent space tensor $\hat{\mathbf{v}}\hat{\mathbf{v}}^T$ from a full rank tensor. Therefore, the normal voting tensor T of a point can be obtained by the direct sum of all the normal space associated with the neighborhood as follows:

$$T(\mathbf{p}) = \sum_{\mathbf{q}\in\mathcal{N}(\mathbf{p})} \frac{1}{\rho_{\mathbf{q}}(\mathbf{p})} \mu_{\mathbf{q}}(\mathbf{p})(\mathcal{I}_{3\times3} - \hat{\mathbf{v}}\hat{\mathbf{v}}^T) \tag{1}$$

where $\mathcal{I}_{3\times3}$ is a 3×3 identity matrix and $\mathcal{N}(\mathbf{p})$ is the k-nearest neighborhood set of a point $\mathbf{p}$ within a range 4δ, where δ is set to the average distance of every point to its very adjacent point. $\rho_{\mathbf{q}}$ represents the ratio of the local density around $\mathbf{q}$ to the maximum density among $\mathcal{N}(\mathbf{p})$ as follows:

$$\rho_{\mathbf{q}}(\mathbf{p}) = \frac{\hat{f}(\mathbf{q})}{\max_{\mathbf{q}_i\in\mathcal{N}(\mathbf{p})} \hat{f}(\mathbf{q}_i)} \tag{2}$$