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Constraint-based point set denoising using normal voting tensor and restricted quadratic error metrics

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ABSTRACT

In many applications, point set surfaces are acquired by 3D scanners. During this acquisition process, noise and outliers are inevitable. For a high fidelity surface reconstruction from a noisy point set, a feature preserving point set denoising operation has to be performed to remove noise and outliers from the input point set. To suppress these undesired components while preserving features, we introduce an anisotropic point set denoising algorithm in the normal voting tensor framework. The proposed method consists of three different stages that are iteratively applied to the input: in the first stage, noisy vertex normals, are initially computed using principal component analysis, are processed using a vertex-based normal voting tensor and binary eigenvalues optimization. In the second stage, feature points are categorized into corners, edges, and surface patches using a weighted covariance matrix, which is computed based on the processed vertex normals. In the last stage, vertex positions are updated according to the processed vertex normals using restricted quadratic error metrics. For the vertex updates, we add different constraints to the quadratic error metric based on feature (edges and corners) and non-feature (planar) vertices. Finally, we show our method to be robust and comparable to state-of-the-art methods in several experiments.

1. Introduction

Point sets arise naturally in almost all kinds of three-dimensional acquisition processes, like 3D scanning. As early as 1985, they have been recognized as fundamental shape representations in computer graphics, [1]. Thus, they have manifold applications e.g. in face recognition [2], traffic accident analysis [3], or archeology [4].

However, during the acquisition process, due to mechanical limitations and surrounding conditions, noise and outliers are inevitably added to the point set. These artifacts have to be removed in a post-processing step to obtain a cleaned point set, which can be used in further steps like surface reconstruction, computer aided design (CAD), or 3D printing. There exists a variety of denoising methods focused on removing outliers and noise from the input point set to create a high fidelity output. These methods do not only aim at removing the undesired components, but also try to preserve sharp features of the geometry. High frequency components like corners or edges should be preserved and not be smoothed out. This is a challenging task as both features and noise are high frequency components and thus ambiguous in their nature.

Most state-of-the-art denoising methods are designed to work on triangle meshes. Compared to this setup, working on point sets and preserving sharp features is more difficult as explicit connectivity information is not present. Also, we assume the input to be given without any normals. However, as point sets take up less storage space and as the surface reconstruction is easier on a noise-free point set, we aim for an intrinsic smoothing method to work directly on the noisy point set input.

Our method is focused on the preservation of sharp features while removing noise and outliers from an input point set. The proposed algorithm follows an iterative three-step point set denoising scheme. (1) Noisy vertex normals processing using a vertex-based *normal voting tensor* (NVT) and *binary eigenvalues optimization* (BEO) similar to [5]. (2) Feature points detection using an anisotropic covariance matrix. For the update of vertex positions, we use (3) a variation of the quadratic error norm adjusted to different kinds of feature points. Steps (1) to (3) are iteratively applied until a satisfactory output has been generated.

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1.1. Related work

1.1.1. Point-based methods

In general, point sets appear as natural output of 3D scan devices. The increase in computational costs while processing polygonal meshes with growing size is partly responsible that points got recognized as primitives for surface representation, cf. [6]. One major drawback in this approach is the absence of connectivity information, which sets the task to declare surface normals. Here, [6] especially proposes a definition utilizing surfels, which are points equipped with normals. Usually point clouds do not carry normals, so we have to rely on methods which determine these robustly and with high quality. The authors Mitra and Nguyen [7] suggest a calculation of point set normals and an analysis under consideration of density, neighborhood sizes, and the presence of noise.

We are interested in point set denoising coupled with feature preservation. There are several works approaching these two properties directly. A first one was published by Fleishman et al. [8] – serving as a representative despite the fact that it deals with meshes instead of point clouds. As it does not use the mesh information, so it can be transferred to the point set setting. They use a bilateral filtering of points in normal direction in local neighborhoods. Another one is the anisotropic smoothing of point sets [9], where the authors use an anisotropic geometric curvature flow. Besides the high dependency on suitable neighborhoods, which the authors cannot compute directly, the proposed algorithm does not detect features explicitly, but incorporates feature detection into an anisotropic Laplacian. The more recent work [10] is based on the idea of sparsity methods and includes L_0 minimization. Originating from image denoising, they set up an energy consisting of the 3D signal to be optimized coupled with an L_0 optimization applied to a differential operator on the signal.

Processing of normals, point positions, and an edge-aware upsampling offers the opportunity for an iterative application. In this setting, we are going to compare our algorithm with that of [11], called "moving robust principal component analysis" (MRPCA). The idea is – like the previous – based on sparsity methods, which takes sparsity-algorithms and adapt them to geometry processing problems. They perceive the point cloud as a collection of overlapping two-dimensional subspaces and do not rely – in contrast to other procedures – on oriented normals as input. The method is robust against outliers and capable of denoising the point cloud while handling sharp features.

Recently, Zheng et al. [12] proposed an extension of edge-aware image processing and mesh denoising to point clouds. In their four-staged approach, feature candidates are detected, employing a feature structure by the l_1-medial skeleton, calculating and equipping these with multiple normals, and selecting guiding normals by using kNN patches with its normals being most consistent. In this terms, the algorithm is even capable of high intensive noise while preserving important geometric features.

1.1.2. Surface reconstruction with feature preservation

One of the processes most affected by noise and outliers in a point set is that of surface reconstruction. A thorough introduction is given in the survey [13]. All following techniques aim at preserving features while simultaneously perform denoising in the surface reconstruction process. In the context of local smoothness priors, the moving least squares (MLS) approach has a major impact. Developed in large parts by Levin [14], MLS underwent a lot of modifications. Guennebaud and Gross [15] modified the MLS idea by replacing the concept of finding well-defined tangent planes by fitting spheres as higher order approximations to the surface. This change makes the method more robust – especially in sparsely sampled regions, where a well defined tangent plane might not exist. Their method is denoted as "algebraic point set surfaces" (APSS) and will serve as comparison to our algorithm. The method of Öztireli et al. [16] aims at overcoming the sensitivity of MLS to outliers and the effect of smoothing out small or sharp features. They combine MLS with local kernel regression to create a new implicit description of the surface, making it robust to noise, outliers, and even sparse sampling. Their method of "robust implicit moving least squares" (RIMLS) will be the third algorithm we compare to. More recently, Chen et al. [17] set their focus on a new MLS formalism using higher-order approximations – like APSS – incorporating discrete non-oriented gradient fields, yielding a continuous implicit representation.

Turning to hierarchical partitioning, Ohtake et al. [18] propose "multi-level partitioning of unity implicits" (MPU). Their technique consists of an octree-based top-down structure, where points in a cell and nearby are approximated by either a bivariate quadratic polynomial or an algebraic trivariate quadric. An adjustment parameter for the level of smoothness guarantees the handling of noise with respect to an error residual tolerance.

Considering piecewise smooth priors and partition based methods, Fleishman et al. [19] concentrate with their robust moving least squares (RMLS) on the handling of sharp features. They use the robust statistics tool of forward-search paradigm to choose small sets of points excluding outliers, continuing through the cloud, and evaluating observations monitored by statistical estimates. Wang et al. [20] robustly compute a feature preserving normal field by mean-shift clustering and a least median of squares (LMS) regression scheme, providing local partitions, to which edge-preserving smoothing is applied by fitting multiple quadrics. Due to the locality, feature fragmentation at sharp edges may occur.

Taking sparsity and neighboring normals into account, Avron et al. [21] use global L_1 optimization on these normals, observing that differences between them should be sparse, yet large values should reflect sharp features. Similar to the approach in RIMLS, [22] suggests the edge-aware resampling (EAR) of the point cloud. This is a feature-sensitive method under the guidance of the locally optimal projection (LOP) [23] in a two-staged approach, starting their robust smoothing and resampling process in regions with similar normal distribution, while approaching the edges in terms of both smoothing and resampling in a second step.

1.2. Contribution

On a noisy point set, it is a challenging task to decouple noise components and sharp features, which is essential for a noise-free point set reconstruction. As shown in Fig. 1, our algorithm consists of three different stages, which are iteratively applied until a satisfactory output has been computed. In the first stage, which is vertex normal filtering, we extend the concept of face normal processing of Yadav et al. [5] to the more general setup of vertex normal processing. Although our vertex normal processing is similar to the face normal processing of Yadav et al. [5], we define a vertex-based *Normal Voting Tensor* (NVT) based on the variation of vertex normals. In terms of noise sensitivity, vertex normals are more sensitive compared to face normals. Therefore, we modify the weighting scheme in the neighborhood selection to make the algorithm robust against different levels of noise. Noise and sharp features are decoupled using the spectral analysis of the vertex-based NVT and noise components are suppressed using *Binary Eigenvalues Optimization* (BEO). In the second stage, we introduce an anisotropic covariance matrix using the filtered vertex normals to detect feature points (edges and corners) robustly on the noisy input point set. In the last stage, we update the vertex positions based on quadratic error metrics. A corresponding quadratic error metric is used based on different feature points. The proposed vertex update

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