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Scalable Curvature-based Feature Detection for Unorganized 3D Point Sets

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Abstract—The information of unorganized 3D point cloud data is limited because of no explicit topologic structure and relations between points. So it is difficult to extract the feature from the 3D point cloud data directly. In this paper, a framework of extracting local salient features from 3D point cloud is presented. We use the geometry properties to detect the features of the 3D point clouds and propose a curvature based multi-scale feature point detection method for unorganized point clouds. Our proposed multi-scale representation for 3D unorganized point cloud is defined in terms of an estimation of point cloud surface curvatures according to local neighborhoods with different sizes. Points corresponding to local extrema of curvature are selected as feature points. We also proposed a quality measure to rank the feature points and select the best ones. Experimental results show that this new approach can detect features effectively and robustly for 3D point cloud data.

keywords-point cloud, feature extraction, muti-scale, quality measure

1. Introduction

The analysis of three-dimensional data is a contemporary research challenge in computer vision and computer graphics. Due to the development of 3D acquisition devices, 3D data can be applied to many tasks such as 3D shape registration [12], and retrieval [1] etc. Such tasks require efficient representation for 3D data in terms of feature points. Various algorithms of extracting feature points for 3D meshes have been developed in the literature [7, 8]. However, for unorganized 3D point clouds, with no explicit topologic connection existing, they can not be directly applied. Therefore, alternative methods using local descriptors to describe the local geometry properties of the 3D data have been presented [13]. In these methods, point locations used for estimating local descriptors are selected either exhaustively at each point or randomly from the data [3]. It is inefficient using the former,and distinctive geometry properties may be missed using the latter.

In this paper, a multi-scale feature extraction algorithm is proposed for unorganized point cloud data based on an estimation of local curvature for each point. Curvature is rotation and translation invariant and reflects the geometric structure of a local region. We estimate the curvature of each point at multiple scale levels by its neighborhoods with different sizes. To do so,we first parameterize the input 3D point cloud data onto plane by minimizing the metric distortion [10]. And the neighbors of each point are those selected within a circle on the plane with multiple radii. By this way, we try to avoid the situation where data points in the same sphere may lie on different surfaces(Figure 1)

(a) 3D point cloud data (b) After parameterization

Figure 1: Neighbors(in pink) of a point v_i(in green) and a point v_j(in red) (a)v_j is a neighbor of v_i in 3D representation. (b)v_j is not a neighbor of v_i after parameterization

(a) input data (b) parameterazation (c) feature points

Figure 2: The process of feature extrcting. (a)Input 3D point cloud data; (b)Parameterazing 3D data; (c)the feature points localized on the 3D point cloud data.

We then construct point cloud curvature octaves,and define a function similar to Difference of Gaussian (DoG) operator used in sift [4], whose extrema in both its neighborhood and in the three consecutive scales are selected as the positions of feature points. Finally,a quality measure for each feature point to rank them so as to find the those with more distinctive geometric structures(Figure 2).

2. Multi-Scale Feature Extraction

In this section we present a novel method for efficient representation of unorganized 3D point cloud data based on multi-scale feature extraction. This work is inspired by the state-of-art schemes such as David Lowe's work for extracting feature points in images. We aim to extend such approach to local feature detector for unorganized point clouds.

2.1. Multi-Scale Curvature Estimation

The 3D point cloud data is given as $V = \{v_i\}_{i=1}^{n}$ and the scale set is given as $S = \{s^k\}_{k=1}^{t}$. We denote the neighbors of a point v_i as $N_i = \{v_{ij}^{r}\}_{j=1}^{m}$, where m is the number of neighboring points and r is the radius for searching neighbors. The tangent plane at point v_i is $Tp(v_i) = r_i \cdot n_i - d = 0$, where n_i is the normal vector at point v_i using neighboring information within radius r_i. n_i is estimated by the following least-square optimization:

$$\min\left(\sum_{j=1}^{m} (v_{ij}^{r} \cdot n_i - d)^2\right) \tag{1}$$

Where $d = |n_i \cdot (p_i - \overline{p}_i)|$ in which $\overline{p}_i = \frac{1}{m} \sum_{j=1}^{m} v_{ij}^{r}$.

This problem can be solved to perform the Principal Component Analysis(PCA) for the covariance matrix [5] below,

$$\mathrm{CV_i} = \begin{bmatrix} \mathbf{v_{i1}} - \overline{\mathbf{v}}_\mathbf{i} \\ \mathbf{v_{i2}} - \overline{\mathbf{v}}_\mathbf{i} \\ \vdots \\ \mathbf{v_{im}} - \overline{\mathbf{v}}_\mathbf{i} \end{bmatrix}^{\top} \begin{bmatrix} \mathbf{v_{i1}} - \overline{\mathbf{v}}_\mathbf{i} \\ \mathbf{v_{i2}} - \overline{\mathbf{v}}_\mathbf{i} \\ \vdots \\ \mathbf{v_{im}} - \overline{\mathbf{v}}_\mathbf{i} \end{bmatrix} \tag{2}$$

Where CV_i is the symmetric positive semi-define matrix. We designate $\lambda_1 \leq \lambda_2 \leq \lambda_3$ as the eigenvalues of the matrix CV_i associated with unit eigenvector e_1, e_2, e_3, respectively. Then we choose the normal of v_i to be either e_1 or $-e_1$.The curvature at point v_i is estimated as [11]

$$H_i = \frac{\lambda_1}{\lambda_1 + \lambda_2 + \lambda_3} \tag{3}$$

For unorganized point clouds, the scale r_i represents the measurement according to Euclidean distance. All the points in the sphere centered at v_i are taken to be neighbor points. The drawback of this method is, when the radius of the sphere is large,the points lacking topologic relations may be considered as in the same neighborhood because of the close Euclidean distance. And in this case, the curvatures estimated by the above method are invalid. In order to obtain an appropriate estimation of curvature, we parameterize the surface of the point clouds onto a 2D plane by minimizing metric distortion. Due to the inherent distance preserving property during the parameterization, the neighbors are determined in a circle centered at v_i. The Euclidean distances between points indicates the geodesic distance between them approximately after parameterization [6]. This strategy to obtain neighbors of each point lead to more robust estimation of curvatures, which reflect the local geometric structures effectively.

2.2. Feature Points Extraction

In 2D image domain,scale-space representation is established and interest points and their scales are detected using the Difference of Gaussian (DoG) operator. For that, we define the point cloud curvature octaves as $H^s = \{H_i^s\}_{i=1}^{n}$, where s is the scale. Consecutive octaves are subtracted to compute the DoG function. The local extrema both in location and scale are considered as feature points. The point cloud curvature octaves are computed by using the different sizes of the neighborhood to estimate the curvature of each point of the 3D data. It is noted that, in equation (2), the size of neighborhood will affect the curvatures. In fact, increasing the size of the local neighborhood is similar to applying a low-pass smoothing filter. With the size of neighborhood increasing,the contribution of each point to the variation decreases [9]. Given two consecutive point cloud curvature octaves,the DoG function l_i^s at scale s is defined as

$$l_i^s = |H_i^s - H_i^{s+1}| \tag{4}$$

Then the feature points are selected as those which are local extrema among their immediate neighbors, both on the current level and two adjacent levels.

To summarize, the process of multi-scale feature points selected can be expressed in a pseudo code format in Algorithm 1.

Algorithm 1 Feature Extrction

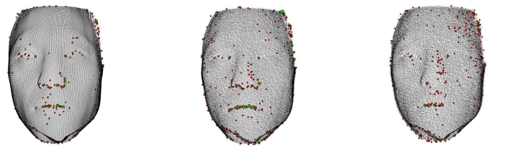
Require:
Set $V = \{v_i\}_{i=1}^{n}$, $v_i \in \Re^3$ for each point of input point cloud data;
Ensure:
Set of feature points F
Begin:
Parameterize the 3D point cloud data onto a 2D plane,and obtain the points' 2D coordinates $U = \{u_i\}_{i=1}^{n}$,where $u_i \in \Re^2$
for $s \in s_k$ **do**
  for $v \in v_i$ **do**
    Find the neighborhood N_i at scale s on the 2D representation of 3D point cloud data;
    Calculate the matrix CV_i in the neighbor N_i;
    Calculate the curvature H_i at point v_i;
    Establish the DoG function l_i
  end for
  The feature points are selected as the points that have local extrema among their neighbors N_i,both on the current scale and two adjacent scales r_{k-1} and r_{k+1}.
end for
End

2.3. Quality Measurement of Feature Points

In this paper, to find good features from a feature point set, we define a quality measure of each feature point at scale r_k to be,

$$Q_i = \frac{D_i}{\sum_{v_j \in N_i} H_j} \tag{5}$$

where D_i denotes the local density around each feature



(a) original (b) $\sigma_G = 0.005$ (c) $\sigma_G = 0.009$

Figure 5: Feature extrcting with the presence of noisy data.

point and is defined as

$$D_i = \frac{1}{|N_i|} \sum_{v_j \in N_i} |H_i - H_j| \tag{6}$$

For v_i to be a good feature point, the value of equation(4) should be much larger than those of its immediate neighbors, ie.the quality of v_i is high. A low quality measure means that the curvature of v_i dose not deviate much from those of its neighbors. Under this condition, the local extrema may happen due to noisy input data rather than any notable geometric structure. It is in this way that the quality measure of each point Q_i can be used to retain more reliable feature points. For example,if Q_i is greater than a threshold τ,v_i is considered as a feature point; otherwise,v_i is a non-feature point.

3. Experiments and Discussions

3.1. Multi-Scale Feature Extracting

We evaluated the effectiveness and robustness of our proposed method on several 3D point cloud data. The detected points in Figure 3 for different 3D models with the same quality measure. The scales used to extracting feature points depend on the geometry of 3D data and were selected empirically, which are indicated by colored spheres. Figure 4 shows the features on the ”T-rex” [2] model using four different quality thresholds respectively. It can be seen that, the higher the quality measure, the more distinctive the geometric property of the feature point is.

3.2. Noisy Data

We tested our method on noisy data by adding Gaussian random noise with standard deviation $\sigma_G = 0.005$ and $\sigma_G = 0.009$ to the input 3D point clouds. Figure 5 shows the points detected from a face model for different levels of noise. Although the local variation will increase from the input noise and the feature points will arise, the features appear in the original model can be detected and localized repeatedly in noisy input data.

4. Conclusions and Future Work

This work introduces a novel framework for extracting multi-scale feature points from unorganized point cloud. Estimation of curvature describe geometric structure of neighborhood in different scales, which were determined by parameterizing the 3D data onto a 2D plane. And a scale-space representation of point cloud data is established by DoG function derived from multi-scale curvature octaves. Feature points are selected as the points having the local extrema in both the current and adjacent levels. Finally, a quality measure is computed to rank the feature points and the best ones are kept.

In the future work, we plan to develop a new type of descriptor for feature points which reflect both the curvature information and spatial geometric structure of a local region at multi-scales. The local feature detection framework will be a preprocessing step for various applications such as 3D shape registration, recognition, retrieval,and classification.

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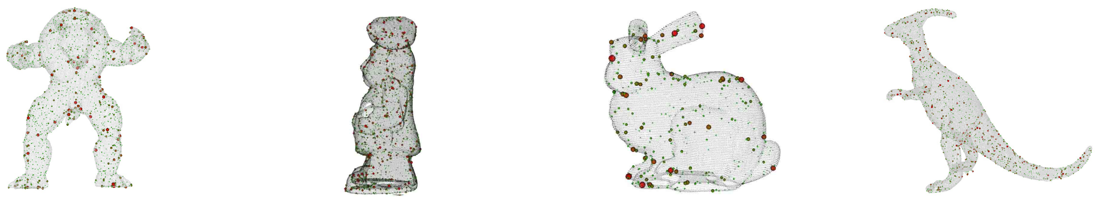
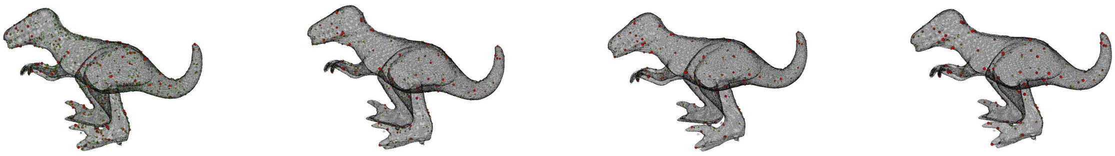


(a) Armadillo (b) Cheff (c) Stanford Bunny (d) Parasaurolophus

Figure 3: Experiments results:feature points of four 3D point cloud data(scales of feature points is expressed in different colors) with the same quality $Q_i > 0$



(a) $Q_i > 0$ (b) $Q_i > 0.0005$ (c) $Q_i > 0.001$ (d) $Q_i > 0.003$

Figure 4: Feature points extracting from model T-rex with four quality measure: (a) $Q_i > 0$, (b) $Q_i > 0.0005$, (c) $Q_i > 0.001$, (d) $Q_i > 0.003$

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