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Apply a Point Cloud Processing Algorithm for Weighted L0

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Abstract

In view of the fact that L0 optimization algorithm is sensitive to the edge and corner points of the point cloud and tends to cause the error of normal estimation, we propose a normal estimation algorithm based on weighted L0. Firstly, according to the Euclidean distance between the points, the distance between the measured points and the field points is calculated as the weight of the distance. Then, we use the Angle difference between the points in the normal direction to calculate the weight. Finally, we add the weight information to the L0 algorithm to find the optimal solution and get the high quality point cloud normal direction. To improve the robustness of the algorithm.

Keywords

Weighted L0; European Distance; Weight Information; Point Cloud Approach.

1. Introduction

Point clouds basically occur in all kinds of 3D acquisition processes, such as 3D scanning. As early as 1985, they were considered the basic shape of computer graphics. Therefore, it is widely used in many fields, such as archaeology, traffic accident analysis, face recognition, virtual reality and so on [1].

The key feature of point cloud is point cloud vector information. Not only do many accurate and high-quality point-based rendering methods rely on legal vector information, but a large number of algorithms for rebuilding point cloud data surfaces also require comprehensive and accurate point cloud vectors to obtain real reconstruction results. Such as the unity of multi-layer implicit surface reconstruction algorithm division, the detection of sharp features and feature recovery are also completely dependent on accurate legal vector information [2].

More than a decade ago, there were a number of excellent algorithms for point cloud vector adjustment for work such as 3D point cloud filtering. In 1992 hoppe et al. proposed the use of PCA fitting planes to determine the law of the point cloud, but the estimation of the point cloud surface of large noise is inaccurate [3]. In 2009 A.C. öztireli et al. mentioned the use of bilateral filtering to process normals, but in some point cloud surfaces with distinct characteristics, feature ambiguity occurs [4]. In 2015, Yujing Sun et al. proposed an algorithm for L0 optimization of the point cloud [5]. The L0 paradigm is the number of non-zero elements that point to the quantity and is directly related to the sparseness of the point cloud. In some noisy point clouds, the algorithm works very well, but in some features of the point cloud, there are some over-optimized results. Therefore, we propose a weighted L0 optimization algorithm for this deficiency.

2. Basic algorithm

2.1 Initial normal estimate

The weighted L0 algorithm we proposed is to optimize the point cloud model with initial normal data and obtain a high-quality point cloud approach. Therefore, PCA algorithm is used here for normal

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estimation of the point cloud containing only point information [6]. and get the initial normal data. First of all, we assume that the local region where any point p in the point cloud can approximate a plane, then the normal direction n of point p can be approximated to the plane by using the domain points in the spherical domain points through least squares fitting, as shown:

$$C = \frac{1}{k}\sum_{i=1}^{k}(p_i - \overline{p})(p_i - \overline{p})^T \tag{1}$$

Here, k refers to the number of points in the sphere of radius r. And the problem of finding the fitting plane can be transformed into the problem of finding the eigenvector corresponding to the minimum eigenvalue of the semi-positive definite covariance matrix C in Equation (1).The method is PCA algorithm.

2.2 L0 normal estimation algorithm and insufficient.

To further optimize the normals, Yujing Sun et al. proposed a method that uses the L0 optimization algorithm to estimate the point cloud normal, and in order to estimate the normals of the point cloud, we assume that the initial normal of the point cloud is $\hat{n}$, and then we minimize the following equation:

$$\min_{n,|n_i|=1} |n - \hat{n}|^2 + \eta|D(n)|_0 \tag{2}$$

Here $D(n)_{ik+j}$=$\mathrm{n}_i - n_{M(i,j)}$ and $M(i,j)$ are the j domain point in the sphere of point cloud p_i. In addition, an auxiliary parameter θ is added to the formula. Therefore, the above formula can be written as follows:

$$\min_{n,|n_i|=1} |n - \hat{n}|^2 + \beta|D(n) - \theta|^2 + \eta|\theta|_0 \tag{3}$$

Here $|n_i| = 1$ is a unit of law, and when $D(n) > \frac{\eta}{\beta}$, $\theta = \frac{\eta}{\beta}$; Instead, $\theta = 0$;

From the above process, we can get a relatively high quality normal n .L0 optimization can achieve the effect of the basic consistency of the normal direction in the same plane, but we do not consider the factor of point-to-point distance here. In the point cloud model, the closer the point is, the greater the influence on its normal direction, and the less vice versa. Here, if the position relationship between points is not taken into account, when the domain points to be measured in the point cloud have a large normal deviation from the normal direction, the optimized normal direction may have a large deviation from the previous normal direction, and the robustness is poor. Therefore, it is necessary to improve the L0 optimization algorithm to enhance its robustness.

2.3 Weighted L0 normal estimation algorithm.

Through the analysis of chapter 2.2 above, we added the distance between points and the angle difference between the verses in the L0 fag optimization algorithm. We used a weighted L0 approach to the point cloud approach to obtain a high-quality point cloud approach. The formula for the algorithm is as follows:

$$\min_{n,|n_i|=1} |n - \hat{n}|^2 + \beta w(p_i)w(n_i)|D(n) - \theta|^2 + \eta|\theta|_0 \tag{4}$$

Here: $w(p_i) = e^{-\left(\frac{|p_i - p_j|}{r}\right)^2}$, $w(n_i) = e^{-\left(\frac{|n_i - n_j|}{0.5}\right)^2}$. here, $w(p_i)$ is the distance weight, When the distance between point p_i and p_j to be measured is smaller, the larger the weight is, and vice versa. Also, r is the radius of the field, which we generally set to 2.43. $w(n_i)$ is the angle weight, When the Angle difference between normal n_i of the point to be measured and normal n_j of the field point is relatively small, the larger the weight is, and vice versa. We perform anisotropic treatments on the normal directions of the points. The normal direction of the point is not completely dependent on the difference between the normal directions, and the robustness of the algorithm is enhanced.

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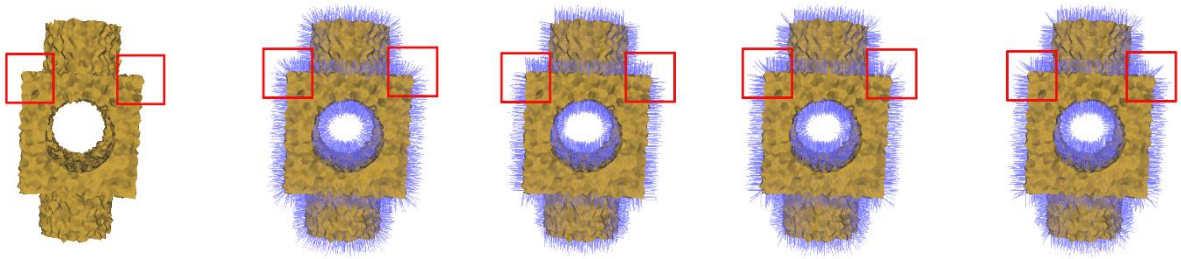
3. Experimental results

PCA, bilateral filtering, L0 normal and weighted L0 normal are respectively applied to carry out normal estimation of cube and block point clouds with noise. The results of normal estimation are shown in Fig. 1,2. The time of normal estimation is shown in Table 1.

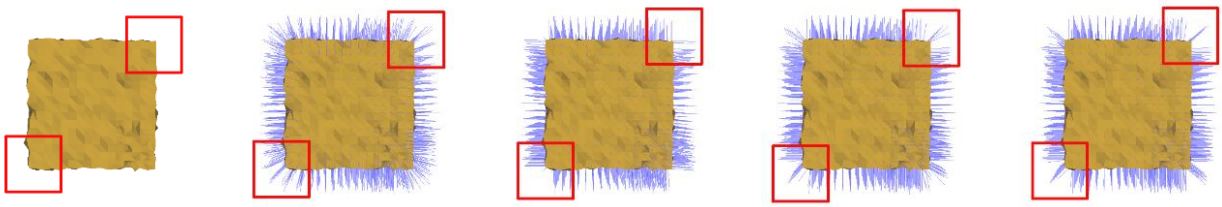
We found from Figures 1,2 that all four method estimation models can estimate better point cloud verses, but at the corners, edges, and other characteristics of the model. We'll see that the point cloud approach estimated by the PCA is dissipated. Therefore, bilateral filtering is processed on this basis, so that the law of the points on the edges is adjusted to the surface, resulting in the reconstructed edges are very flat and blurred features. The L0 algorithm solves this problem, but for some noisy points on the edges, the legal adjustment is not very clear. Therefore, our algorithm adds weight information to make the L0 algorithm robust. Better estimate of high-quality point cloud approach.

In Figure 3,4, we reconstruct the surface of the point cloud for the three models, and we find that the PCA algorithms in Figure 3(a), 4(a) blur some important features such as edges, corners, and so on. Makes the model smooth and not sharp. Figures 3(b),4(b) are bilateral filters, and we find that the points on the edges move to the two planes of the point cloud, causing the surface to rebuild, where the edge is not a straight line, but a tiny plane. Therefore, with the Weighted L0 algorithm of Figure 3(c), 4(c), the algorithm retains the characteristic information of the point cloud and has good robustness.



(a) The original (b)PCA (c) Bilateral (d) L0 (e) Weighted L0

Fig. 1 Block normal comparison



(a) The original (b)PCA (c) Bilateral (d) L0 (e) Weighted L0

Fig. 2 Cube normal comparison

From the analysis in Table 2, we conclude that the algorithm of weighted L0 takes a long time, because in the process of optimization, the European distance between points needs to be calculated, and the difference between the errations is used as the weight information. Therefore, the results calculated are more accurate than larger than among other algorithms, but take more time.

Table 1. Time comparison

Point cloud	Scores	PCA	Bilateral	L0	Weighted L0
cube	1906	0.03	0.33	13.93	15.23
block	8771	0.23	2.71	103.24	124.32

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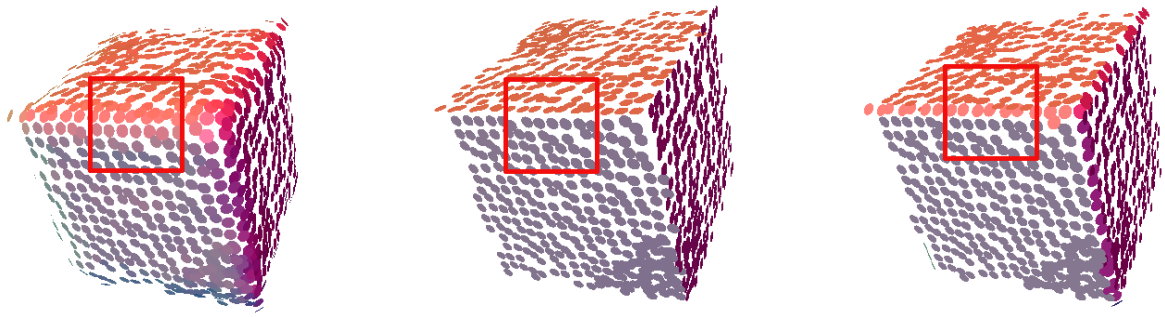
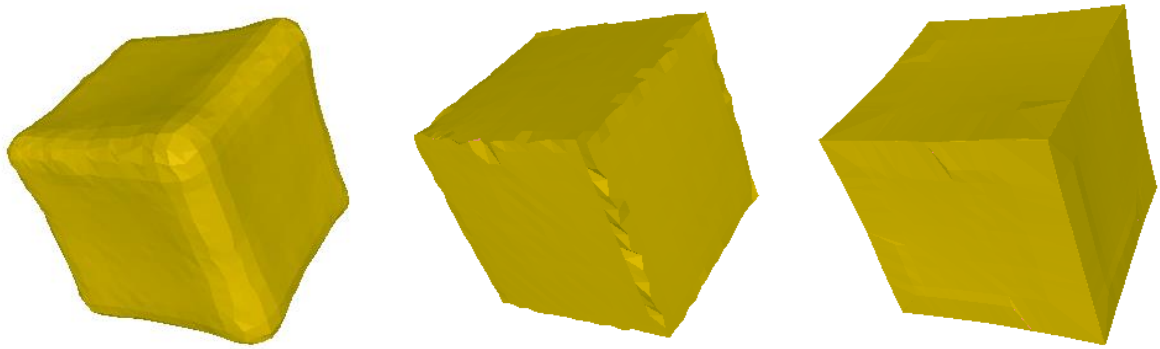


(a)PCA (c) Bilateral (e) Weighted L0

Fig. 3 Cube The method is compared in a directional direction



(a) PCA (c) Bilateral (e) Weighted L0

Fig. 4 Cube Surface reconstruction comparison

4. Error analysis

To quantify the feature part, we examine the normal error between the denoising model and the original model. We use the average Angle error to measure the error between normal directions, which is defined as follows:

$$MAD = \frac{1}{N}\left(\sum_{i=0}^{N-1} \measuredangle(n_i^o, n_i^d)\right) \tag{5}$$

Here: n_i^o and n_i^d are respectively the point normal of the original model and the point normal of the denoising model. N is the total number of point clouds.

Table 2. Average error comparison(second)

Point cloud	PCA	Bilateral	L0	weighted L0
Block	8.681	6.125	5.638	4.512
Cube	3.763	2.662	0.944	0.846

5. Summary

In this paper, a general estimation algorithm based on weighted L0 optimization is proposed. Based on the distance between points and the difference between the errations as a weight, L0 is optimized to obtain a relatively high-quality point cloud approach. The experimental results also prove the effectiveness of the algorithm. You can get high-quality point cloud approach. However, the algorithm is used in the sphere, the radius size needs to be artificially set, and the preset value may

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affect the estimation of the final law. The next step is to focus on how to adapt the radius based on point cloud data.

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