Research on denoising optimization algorithm of point cloud in 3d reconstruction

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Abstract. 3d reconstruction have become increasingly important in today's information age, has become a bridge between real world and computer, usually in the access to the image due to factors such as equipment or environment are people hope there are a large number of high frequency signal, the pretreatment of the 3d reconstruction is the most basic and crucial step in the technology. In this paper, an optimized adaptive filtering de-noising algorithm is proposed. The concept of minimum intra-class dispersion is introduced into the algorithm, and the genetic algorithm is used to find the optimal threshold, so as to eliminate the disadvantages of the algorithm in searching the scattered point cloud data and promote the overall performance of the algorithm. In this paper, the algorithm improves the speed, simplifies the initial point cloud model, and eliminates a large number of invalid points from the subsequent filtering algorithm.

1. Introduction
Three-dimensional reconstruction is the link between the real world and the virtual world, and has become a hot topic in many fields of research. It opens up new research opportunities for computer vision, robotics and other cutting-edge technologies, and it is also a great challenge facing mankind. 3d reconstruction technology has been widely used in artificial intelligence, medical imaging, industrial measurement [1-2], virtual reality and other fields. Point cloud data acquisition, neighborhood search, filtering, feature extraction, matching and reconstruction are the main processes of three-dimensional reconstruction [3].

There are many ways to obtain the initial point cloud data of 3d reconstruction. Generally, the obtained data are scattered points and the geometric features of the curved surface are not obvious. Using the relationship between points, the irregular data is firstly processed [5-6].

Processing is a key step in 3d reconstruction [7]. Neighborhood search algorithm as a 3d reconstruction technology

Therefore, the research on neighborhood search algorithm is of great importance. Generally, images acquired by 3D devices are affected by acquisition, storage, processing and various interferences due to factors such as equipment, environment or objects under test. As a result, there will be some high-frequency signals in the acquired images, which will greatly hinder the subsequent reconstruction work. In order to process the above point cloud data, the first step is to filter the noise, that is, the filtering algorithm. This process should achieve two points: as much as possible to filter noise; The original details are kept as much as possible while de-noising so that the data will not be distorted due to filtering. Point cloud filtering can be reduced to image processing. The technology first appeared in the 1950s.

At that time, people can already use computers to do some simple image processing, and the computer at that time has been out of the primary level. In the 1970s, image processing technology also developed by leaps and bounds along with the progress of the information age, marching to a higher
level. In the 3D reconstruction technology, the filtering and denoising technology has also been deeply applied. The images obtained in 3D reconstruction basically include spectral, spatial and other information. For grayscale images, color information is reflected by the grayscale value of pixels. In 3D reconstruction technology, geometric information and feature details of the object under test are reflected in the initial image of point cloud. For example, for the edge of an object whose pixel value changes sharply, the depth information in the depth image may also change sharply. These edges generally present high-frequency features, but the pixel value inside the object keeps fluctuating within a certain range, which is more uniform and presents at a low frequency. Therefore, the high frequency enhancement of the obtained image is called high pass filtering. On the contrary, filtering in the region with little fluctuation of image pixels completes the smooth region, which is a low-pass filtering.

2. Adaptive neighborhood search window algorithm

In order to speed up filtering speed, remove background and reduce computation, k-nearest neighbor search algorithm of pixel points is firstly carried out before filtering algorithm. The three-dimensional point cloud model is mapped to the plane to obtain the point cloud model on the coordinate plane. According to the 3D map obtained by 3D camera, the foreground number is obtained within the index range of point cloud. Its calculating process, the first thing to stay in the current surface to find the point P neighborhood of the point P, to find in the current neighborhood within the point cloud point set point, there are usually two ways, first, based on the circular search way, at a certain radius, to find and to calculate points from the nearest point, a circle a circle. Second: set the number of points in the neighborhood set. First, traverse the point cloud, sort the distance between all points in the point set and the current point, and take the first K points with the smallest distance as the points in the neighborhood set of P.

Foreground coordinate detection dimension R/K microns, that is, the ratio of the radius of the query point to the number of points in the neighborhood. Calculates the search window edge length centered on the query point and USES the index number of that edge length to describe the scope. Establish a mapping to realize the connection between the index of pixel points and the index of search window, and create the search window with query points. In the current window, K points closest to the point to be calculated are searched, and the sum of k-neighborhood sets is finally formed. According to the density of the initial point cloud, the edge length of the search window corresponding to it was calculated, and then a fast k-nearest neighbor set search was conducted. When the appropriate window edge length is obtained, by comparing the index of each pixel point in the point cloud with the index of the search window, the neighborhood set search of all points is completed in the window that moves with the points to be calculated.

The initial data of this algorithm is obtained by Kinect and is ordered data. If other 3D cameras are used, the data obtained are disordered point clouds. Scattered point clouds need to be modified on the data structure before searching the neighborhood set. Direct ordered data can directly estimate the relationship between points, which makes neighborhood algorithm faster. The image obtained by Kinect device is very uniform in density on a two-dimensional plane. Due to the low precision of the equipment, when scanning the surface, the object often has obvious fluctuation at the same point. But its hardware is cheap, so it is widely used. Aiming at the data obtained by Kinect, it is of practical value to develop a faster and more accurate neighborhood search algorithm. In the neighborhood search algorithm, the fluctuation of each point should be processed accordingly to reduce the impact of fluctuation, and the computation amount of subsequent filtering algorithm will also be greatly reduced.

3. An optimized adaptive filtering de-noising algorithm

In the traditional denoising algorithm, only gray information of pixel points is considered, and the influence of surrounding pixel points is not taken into account. Therefore, large errors often occur when denoising. The essence of the largest inter-class method used in the traditional three-dimensional point cloud denoising algorithm is threshold segmentation method. The core content of this method is as follows: set the image as \( f(x, y), (1 \leq x \leq M, 1 \leq y \leq N) \), the gray level of the image as L, and the size
as MXN, while the neighborhood smooth image can be obtained by using the average gray level value of the neighborhood of pixel point \( n \times n \), and the gray level of \( g \) is also \( L \). In this way, in each pixel of the image, a binary group can be formed, that is, the gray value of both the pixel and the adjacent domain of the image. \( f_{ij} \) is used to represent the number of \( i \) gray value in image \( j \) and the number of \( j \) pixels in the neighborhood gray value at the same spatial position. The joint probability density is:

\[
P_{ij} = f_{ij} / M \times N \tag{1}
\]

In the above formula, it satisfies \( 0 \leq i, j \leq (L - 1) \), \( \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} p_{ij} = 1 \).

The gray level of the image is:

\[
g(m,n) = \frac{1}{k \times k} \sum_{i=(k-1)/2}^{(k-1)/2} \sum_{j=(k-1)/2}^{(k-1)/2} f(m+i,n+j) \tag{2}
\]

The threshold value of gray segmentation is \( s \), and the gray value of the neighborhood is \( t \). \((s,t)\) is used to divide the image into two categories, namely background and target. At this time, the proportion of background and target in the image can be calculated.

The background is as follows:

\[
\omega_b = \sum_{i=1}^{s} \sum_{j=1}^{t} p_{ij} = \omega_b(s,t) \tag{3}
\]

The objectives are:

\[
\omega_o = \sum_{i=s+1}^{L} \sum_{j=t+1}^{L} p_{ij} = \omega_o(s,t) \tag{4}
\]

Since the noise and the edge point are very small, the noise and the edge point can be ignored, and the situation away from the diagonal cannot be considered. At this point, \( \omega_b + \omega_o = 1 \) can be set, and the mean vector of the two classes is:

\[
\mu_b(s,t) = (\mu_{b1}, \mu_{b2})^T = \left[ \frac{\sum_{i=1}^{s} \sum_{j=1}^{t} ip_{ij}}{\omega_b(s,t)}, \frac{\sum_{i=1}^{s} \sum_{j=1}^{t} jp_{ij}}{\omega_b(s,t)} \right] \tag{5}
\]

\[
\mu_o(s,t) = (\mu_{o1}, \mu_{o2})^T = \left[ \frac{\sum_{i=s+1}^{L} \sum_{j=t+1}^{L} ip_{ij}}{\omega_o(s,t)}, \frac{\sum_{i=s+1}^{L} \sum_{j=t+1}^{L} jp_{ij}}{\omega_o(s,t)} \right] \tag{6}
\]

The total mean is:

\[
\mu(s,t) = (\mu_1, \mu_2)^T = \left[ \sum_{i=1}^{L} \sum_{j=1}^{L} ip_{ij}, \sum_{i=1}^{L} \sum_{j=1}^{L} jp_{ij} \right] \tag{7}
\]

The dispersion matrix is:

\[
\sigma_y = \omega_b [(\mu_b - \mu)(\mu_b - \mu)^T] + \omega_o [(\mu_o - \mu)(\mu_o - \mu)^T] \tag{8}
\]

The method of measuring the distance between the background and the target class using the above dispersion matrix is as follows:

\[
t^r(\sigma_y) = \omega_b [(\mu_{b1} - \mu_1)^2 + (\mu_{b2} - \mu_2)^2] + \omega_o [(\mu_{o1} - \mu_1)^2 + (\mu_{o2} - \mu_2)^2] \tag{9}
\]
Since the calculation amount is too large when point cloud data is de-noised, this paper will improve the algorithm, improve the performance of the algorithm and reduce the computational amount of the algorithm.

Threshold selection is the key to using the denoising threshold method, if the value of the threshold selection is too small, they may become a target background section, if the threshold is too high, then the target is likely to be the background points, denoising threshold is the point of the precision, if not enough quasi accurate can cause error, thus losing useful information, so denoising threshold selection is very important.

In the traditional algorithm, the variance of foreground and background is taken into account, and the cutting effect is also better. However, the discretization within the class is not taken into account, so the classification cannot be fully reflected. In order to improve this situation, intra-class dispersion is introduced in this paper, so as to achieve the maximum inter-class variance and achieve intra-class consistency in segmentation.

The classification discrete measure corresponding to the pixel gray value is expressed as:

\[ \tau_{oi} = \omega_s d_{oi} + \omega_b d_{bi} \]  
(10)

\[ d_{oi} = \sum_{i=0}^{s} \mu_{oi} - i |U_i / \omega_b, d_{bi} = \sum_{j=t+1}^{l-1} \mu_{bj} - j |U_j / \omega_b \]  
(11)

The classified discrete measure of gray value of adjacent regions is:

\[ \tau_{oj} = \omega_s d_{oj} + \omega_b d_{bj} \]  
(12)

The above formula satisfies:

\[ d_{oj} = \sum_{j=0}^{t} \mu_{oj} - j |V_j / \omega_b, d_{bj} = \sum_{j=t+1}^{l-1} \mu_{bj} - j |U_j / \omega_b \]  
(13)

Based on the above, it can be concluded that the one-dimensional inter-class variance corresponding to pixel gray value I is as follows:

\[ \sigma_{bi}(s) = \omega_b (\mu_{oi} - \mu_I)^2 + \omega_s (\mu_{bi} - \mu_I)^2 \]  
(14)

The one-dimensional inter-class variance corresponding to the gray value j of the adjacent region is:

\[ \sigma_{bj}(t) = \omega_b (\mu_{oj} - \mu_J)^2 + \omega_s (\mu_{bj} - \mu_J)^2 \]  
(15)

The optimal thresholds for the two categories should meet the following conditions:

\[ \sigma_{bi}(s) = \max_{0<s<L-1} \{ \sigma_{bi}(s) \}, \sigma_{bj}(t) = \max_{0<s<L-1} \{ \sigma_{bj}(t) \} \]  
(16)

In this paper, genetic algorithm is used to obtain the appropriate threshold vector (s,t) to quickly determine the de-noising threshold.

(1) initialization
Use random Numbers to generate a random row size, 16 column matrix as the initial population.

(2) coding
The threshold to be segmented by two-dimensional Otsu algorithm is two-dimensional, so 16-bit binary code is used to segment the threshold of two-dimensional segmentation. The first eight bits represent the segmentation threshold s, and the last eight bits represent the segmentation threshold t.

(3) fitness function
Use formula (17) and formula (18) to extract the corresponding parameters s and t when the maximum value is obtained, that is, the segmentation threshold we need.

(4) selection
Use fitness proportion method to select, the higher the fitness, the higher the probability of being selected.

(5) crossover
In this paper, the adaptive crossover probability is used. The rule is to give a lower probability to individuals whose fitness is higher than the average, and a higher probability to make them naturally obsolete.
(6) variation
A small probability is used to randomly change the value of a single bit in a chromosome string.

When the gray complexity of the image is L, the algorithm complexity of this paper is \( O(L + L) = O(L) \), far less than the complexity of the traditional point cloud data denoising algorithm \( O(L^4) \), greatly improving the performance of the algorithm.

4. Conclusion
In this paper, an optimized adaptive filtering de-noising algorithm is proposed. The concept of minimum intra-class dispersion is introduced into the algorithm, and the genetic algorithm is used to find the optimal threshold, so as to eliminate the disadvantages of the algorithm in searching the scattered point cloud data and promote the overall performance of the algorithm. In this paper, the algorithm improves the speed, simplifies the initial point cloud model, and eliminates a large number of invalid points from the subsequent filtering algorithm.

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