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Research on Point Cloud Filtering Data Processing Method Based on Self-adaptive Euclidean Clustering Network

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Abstract: *Nowadays, with the development of 3D filtering information processing by data algorithms, people have deeply studied 3D data processing. A series of issues were found in the research process. Moreover, the current research on point cloud data in the use of lidar is not comprehensive. Its research focuses on noise reduction and data block segmentation of point cloud-filtered data. Based on the above background, this paper analyzes the bilateral characteristics of point cloud filtering data in detail. It improves the adaptive clustering network to cluster the sample center points of the point cloud filtering data, effectively improving its readability and processing characteristics.*

Keywords: *Point cloud filtering; Self-adaptive algorithm; Euclidean clustering; Convolutional neural network*

1. Introduction

On the basis of the in-depth study of data processing algorithms, significant progress has been made in studying sample data with different characteristics. People deal with three-dimensional data more deeply. However, the research process has also found a series of problems. The point cloud data generated by lidar is scattered, so finding the center point of clustering samples is challenging. In addition, the cloud coordinates calculation of the sample center point are relatively complex, and the computer can not effectively process this kind of data [1].

Moreover, the research on the point cloud data generated using lidar is focused on the point cloud filtering data denoising and data block segmentation, and the research is currently insufficient. Based on the above background, this paper analyzes the bilateral characteristics of filtered point cloud data, studies the characteristics of data segmentation and classification in detail, and gives the algorithm proof. In addition, the improved clustering of sample center points can effectively improve data's readability and processing characteristics [2].

2. Research on Neighborhood Search Methods for Point Cloud Filtering Data Processing

The principle of the pulse detection method for the point cloud filtering Euclidean modified adaptive clustering data is to emit laser pulses from the laser to the data target and then return from the data target to the receiver. Calculate the time difference $\widetilde{\mathrm{N}}$ and pulse interval τ of the optical pulses of the product of the number of clock pulses of the self-adaptive clustering data, and calculate the distance R as shown in formula (1):

$$\mathrm{R} = \frac{1}{2}cn\pi = \frac{c}{2f}n = \ln \tag{1}$$

Where f is the clock pulse frequency of point cloud filtering Euclidean improved adaptive clustering data. l represents the distance datum for each data clock pulse and n is the number of clock pulses for adaptive clustering data. Then the distance R of the point cloud filtering Euclidean

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improved adaptive clustering data target is obtained.

3. Research on Statistical Data Processing Algorithm of Point Cloud Filtering

A raster method for data processing of point cloud filtering Euclidean improved self-adaptive clustering statistics is to use a small cube to divide the point cloud and calculate the statistical data according to a certain cube side length. We set a cube whose side length is L, and call it a statistical data processing grid. Calculate the number of cubes divided by the overall point cloud in the directions of x, y, and z, which is followed by the processing grid. First, the lowest point cloud filtering Euclidean improved adaptive clustering statistical data processing cuboid surrounding the point cloud data is obtained. After defining the grid side length L, the minimum cuboid is divided into several data processing grids with side length L. Where l_x, l_y, l_z represents the number of grids processed by point cloud filtering in the x、y、z directions, respectively. l_x, l_y, l_z are calculated as follows:

$$l_x = \frac{|x_{\max} - x_{\min}|}{L} \tag{2}$$

$$l_y = \frac{|y_{\max} - y_{\min}|}{L} \tag{3}$$

Moreover, the system architecture of our point cloud filtering statistical data is presented in Figure 1.

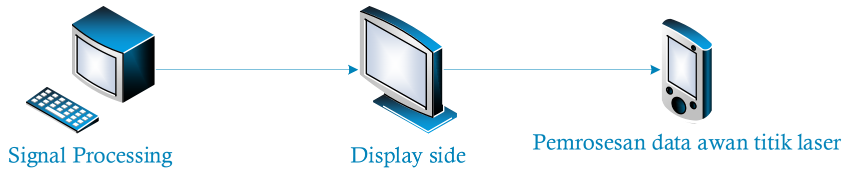

Figure 1: Point cloud filtering statistical data system

4. Data Processing Algorithm for Point Cloud Filtering Based on Improved Adaptive Euclidean Clustering Network

4.1 Research on Random Consistent Point Cloud Filtering Method

Random consistent point cloud filtering European improved adaptive clustering system carried in various mobile systems (cars, aircraft, drone, etc.), the air and vegetation to the water to emit laser. Random consistent point cloud filtering Euclidean enhanced adaptive clustering radar scanner receives the returned laser pulse and records the distance and angle [3]. The quantities of the measured points and echoes are influenced by the scanning speed of the LiDAR system, whose resolution and range depend on different optical instruments and scanners. The main principle of random consistent point cloud filtering Euclidean improved adaptive clustering radar scanner is the random consistency point cloud filtering Euclidean improved adaptive clustering laser ranging. In the formula, D is the distance to be measured, t is the round-trip time to the target, and c represents the propagation velocity of light in the vacuum, which is $3\times10^8 \mathrm{m/s}$.

$$\mathrm{D} = \frac{1}{2}ct \tag{4}$$

The composition diagram of the random consistent point cloud filtering system is shown in the following figure 2.

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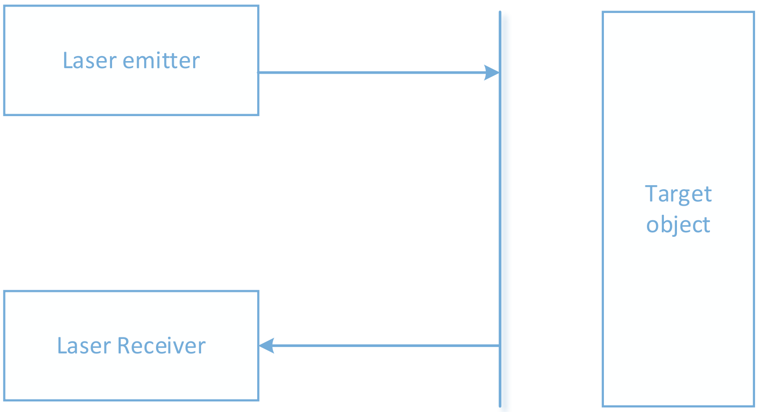

Figure 2: Schematic diagram of the point cloud filtering system with random consistency

In general, laser point cloud filtering Euclidean improved adaptive cluster ranging has two types: pulse-echo type and phase shift type. In pulsed point cloud filtering, enhanced adaptive clustering ranging, c represents the speed of light, S means the distance of random consistent point cloud filtering, t is the pulse propagation time, and N indicates the number of integer cycles included in the light wave propagation process:

Distance of Random consistent point cloud filter:

$$\mathrm{R}=\frac{1}{2}c\cdot t_{L} \tag{5}$$

Distance resolution of random consistent point cloud filtering:

$$\Delta\mathrm{R}=\frac{1}{2}c\cdot\Delta t_{L} \tag{6}$$

Distance accuracy of random consistency point cloud filtering:

$$\delta_{R}=\frac{1}{2}t_{\text{rise}}\cdot\frac{1}{\sqrt{s/N}} \tag{7}$$

Maximum random consistent point cloud filtering distance:

$$R_{\max}=\frac{1}{2}c\cdot t_{L_{\max}} \tag{8}$$

In the ranging principle of the phase method, $\varnothing$ means the phase difference; T is the period, and N means the whole number of cycles in the propagation process [4]. The phase difference propagation time is:

$$\begin{cases}T=2\pi\\ t_{L}=\varnothing\end{cases}\rightarrow t_{L}=\frac{\varnothing}{2\pi}\cdot T \tag{9}$$

Distance of Random consistent point cloud filter:

$$\mathrm{R}=\frac{1}{2}c\cdot\frac{\varnothing}{2\pi}\cdot T=\frac{\lambda}{4\pi}\cdot\varnothing \tag{10}$$

Distance resolution of random consistent point cloud filtering:

$$\Delta\mathrm{R}=\frac{\lambda_{\text{short}}}{4\pi}\cdot\Delta\varnothing\ \$ \tag{11}$$

Distance accuracy of random consistent point cloud filtering:

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$$\delta_R = \frac{\lambda_{\text{short}}}{4\pi} \cdot \frac{1}{\sqrt{s/N}} \tag{12}$$

4.2 Research on Euclidean Clustering Algorithm of Point Cloud Filtering

In the point cloud filtering Euclidean clustering algorithm space R^{m}, there is data $x_i = \{x_{i1}, x_{i2}, \cdots, x_{im}\}, x_j = \{x_{\mathrm{j}1}, x_{\mathrm{j}2} \cdot\!\cdot\!\cdot, x_{jm}\}$ The Euclidean distance is:

$$d\left(x_i, x_j\right) = \| x_i - x_j \| = \sqrt{\sum_{i=1}^{m} \left(x_i - x_j\right)^2} \tag{13}$$

For the data sets x_i and x_j in the Euclidean clustering algorithm space R^{m}, $\mathrm{i, j}$ represents the index of different points. The $D = \{x_1, x_2, \cdots, x_n\}$ represents the dataset which contains n point cloud filtering Euclidean clustering data objects. Moreover, $D_{n^* n}$ is a distance distribution matrix of data set D, namely:

$$D_{n*n} = \left\{d\left(x_i, x_j\right) | 1 \le i \le n, 1 \le j \le n\right\} \tag{14}$$

In the point cloud filtering Euclidean clustering algorithm space R^{m}, there is a point cloud filtering Euclidean clustering data set $D = \{x_1, x_2, \cdots, x_n\}$ containing n point cloud filtering Euclidean clustering data objects, and the Eps neighborhood parameter η is set as:

$$\eta = \sqrt[4]{n} + 1 \tag{15}$$

In the point cloud filtering Euclidean modified adaptive clustering algorithm space R^{m}, the $D = \{x_1, x_2, \cdots, x_n\}$ represents the dataset containing n point cloud filtering Euclidean clustering data objects.

$\mathrm{D}_{\mathrm{n}n}\mathrm{n}$ is the distance distribution matrix of the data set D. The η-th smallest distance parameter $\mathrm{d}\left(\mathrm{x}_{\mathrm{i}\eta}\right)$ is taken from each row of the distance distribution matrix. Then, the distance array D_η is obtained.

$$D_\eta = \left\{d\left(x_{i\eta}\right) | 1 \le i \le n, \eta = \sqrt[4]{n} + 1\right\} \tag{16}$$

The Eps neighborhood distance is:

$$\text{Eps} = \overline{D_\eta} = \frac{1}{n} \sum_{i=1}^{n} d\left(x_{i\eta}\right) \tag{17}$$

Algorithmic data cluster analysis and intelligent identification in point cloud filtering are mainly based on improved adaptive Euclidean networks. This improved adaptive Euclidean network requires the following steps to adapt to the application and clustering process [5]. First, we need to obtain the neural network's pattern signal and feature extraction. Then train and extract sample eigenvalues. We then train an improved adaptive Euclidean network to make the algorithm perfectly applicable to the data clustering process of point cloud filtering algorithms. Next, classify and sample samples using a trained extended self-adaptive Euclidean network. Different output values are utilized to evaluate the network performance of the corresponding classification results [6].

4.3 Research on Data Segmentation of Point Cloud Filtering Algorithm

Reflecting objects have a specific correlation. The radiative transfer equation of point cloud filtering lidar is as follows:

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$$P_s = \frac{P_i D_r^2}{4\pi R^4 \beta_t^2} \lambda_{\mathrm{sys}} \lambda_{atm} \sigma \tag{18}$$

In the formula: P_i represents the power of point cloud filtering and adaptive clustering data segmentation and processing radar transmission signal; P_s represents the power of the received object reflection point cloud filtering European-style adaptive clustering data segmentation and processing echo signal; R represents the distance between target and data segmentation processing radar. D_r is the data segmentation processing radar receiving aperture; β_t means the data segmentation processing divergence angle. λ_{atm} means the influence factor of the signal in atmospheric transmission; λ_{sys} represents the radar system parameters in data segmentation and processing; σ is the backscattering cross-section, which is related to the reflection characteristics of ground objects. (See figure 3)

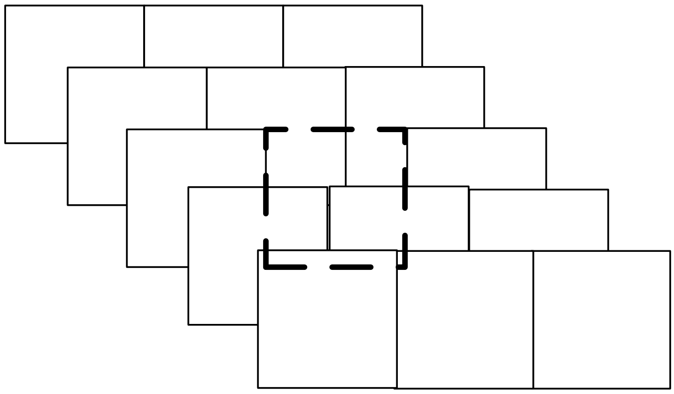

Figure 3: Schematic diagram of data segmentation grid using grid method of point cloud filtering

The adaptive improved Euclidean clustering algorithm applies the system reconfiguration of the enhanced Euclidean clustering network to carry out short-term memory and calculation of pattern recognition. Furthermore, the corresponding weight values of convolution layers are obtained through the network training process. Considering the fact that the local features are too small to be observed [7], the simulated annealing algorithm is utilized to boost its performance. Moreover, the local gradient descent method also contributes to the improvemrnt of its efficiency and effectiveness.

4.4 Processing of Improved Adaptive Classification in Point Cloud Filtering Algorithm

In the improved adaptive classification Euclidean space R^{m}, the enhanced adaptive classification D of the point cloud filtering algorithm contains n data objects: $D=\{x_1,x_2,\cdots,x_n\}$. The category D is divided into k independent clusters: $C=\{C_1,C_2,\cdots,C_k\}$. The center point of each cluster is $\{v_1,v_2,\cdots,v_k\}$. The global center of improved adaptive classification of point cloud filtering algorithm D is $v_{\text{¡£Àà´Ø}} C_i$. The data objects contained in Ci is $|C_i|$. Then the clustering effectiveness index CSI of the clustering partition is defined as:

$$CSI=\frac{\mathrm{Cop}}{Sep}=\frac{S-T}{S+T}=\frac{\frac{1}{k-1}\sum_{i=1}^{k} d(v_i,v)^2 * |C_i| - \frac{1}{n-k}\sum_{i=1}^{k}\sum_{x\in C_i} d(x,v_i)^2}{\frac{1}{k-1}\sum_{i=1}^{k} d(v_i,v)^2 * |C_i| + \frac{1}{n-k}\sum_{i=1}^{k}\sum_{x\in C_i} d(x,v_i)^2} \tag{19}$$

Figure 4 shows the improved adaptive classification process of the point cloud filtering algorithm.

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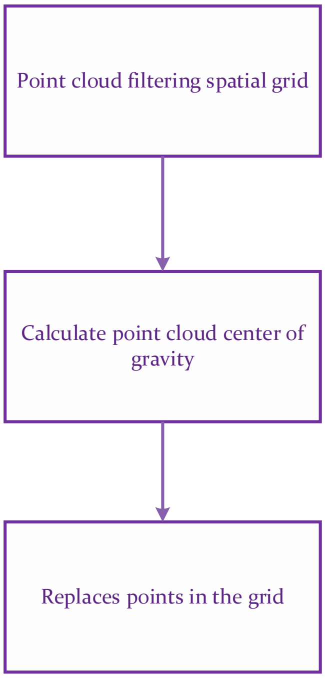

Figure 4: Improved adaptive classification process of point cloud filtering algorithm

Currently, the research on the adaptive classification data of point cloud filtering algorithms mainly focuses on analyzing point cloud filtering databases. The main research topic is primarily the point cloud classification, data compression and storage efficiency. Given this, the current point cloud filtering technique is mainly adopted to calculate, classify and compress the point cloud points. In addition, the detailed research on the point cloud filtering data in the classification process is also available. Nowadays, point cloud filtering data mining algorithm is mainly applied to work with point-cloud data on the enhancement of its classification and feature extraction. For specific fields, the specific methods of processing and organizing the point-cloud data is also essential to acquire excellent performance [8].

Based on traditional data classification algorithms using point cloud filtering, a new data classification method with improved adaptive Euclidean clustering is proposed in this paper. This method mainly uses kernel functions to group bad samples in point cloud filter data [9]. It improves traditional neural networks' clustering performance, accuracy, and error identification accuracy by allowing mathematical mapping to map the eigenvalues into a high-dimensional space and perform fuzzy clustering. The clustering method quickly distinguishes the clustering scheme from the anomalous point cloud-filtered data. After clustering the data with the mentioned algorithm, the point cloud-filtered data obtained by the clustering scheme has many outliers and missing values. The outliers and missing clustering values for these clustering schemes need to be addressed [10]. In order to deal with the missing values of the point cloud filtering scheme, three measures are mainly applied to prevent the above mentioned problems, including deletion, filling, and processless methods. In this paper, the clustering scheme is utilized to get the favorable outputs, where the outliers are deleted and treated as the missing values outside the clustering scheme. In addition, the method of interpolating the point cloud filtering data of the clustering scheme is also adopted to fill in the missing values.

5. Conclusion

Based on the characteristics of point cloud filter data, this paper analyzes the bilateral characteristics of point cloud filter data in detail. It focuses on building an example center point in the algorithmic processing of point cloud filter data. We enhance a self-adaptive clustering network that clusters sample centers in point cloud-filtered data, effectively improving the readability and processing properties of the data. In addition, the processing speed of point cloud filter data has been dramatically improved.

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