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Automatic Classification of Transmission Lines Based on Edge Detection Filtering Algorithm and Laser Point Cloud Data Processing

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ABSTRACT

Aiming at the problem of low automation and accuracy of semantic segmentation of transmission line point cloud data, an automatic segmentation algorithm of point cloud data that can extract objects such as towers, ground wires, and conductors is proposed based on the spatial feature distribution and edge detection filtering algorithm of the transmission line. The power plant is being tested using cloud data from the overhead power line LiDAR obtained from a drone. The results show that the algorithms proposed in this document have high accuracy and memory. The precision of the tower, conductor, and ground wire is 99.74%, 99.22%, and 97.69%, respectively, and the recall is 95.08%, 100%, and 97.97%, respectively. The classification effect is better than the commonly used automatic classification software of transmission line point cloud. Therefore, it has significant application value for realizing the accurate extraction of power lines and towers in transmission line point cloud data.

Index Terms—Airborne lidar, edge detection and filtering, semantic segmentation, tower and power line, transmission line classification

I. INTRODUCTION

As Mongolia's electricity sector develops rapidly, the distribution network becomes more dense, which poses major challenges to transmission line inspections. The classification process of the background target of the transmission line is that the Unmanned Aerial Vehicle (UAV) video acquisition module uses the UAV equipped with video acquisition equipment to obtain the image information of the background area of the transmission line, and the neural network preprocessing module performs Deep belief network (DBN) network training on the image to obtain the initial parameters for saliency detection. The target detection module uses the Stacked Denoising Auto Encoder (SDAE) network to obtain the reconstructed image and matches the original image to obtain the saliency target calibration map. To address the high risk and inefficiency of traditional manual testing methods [1, 2], unmanned inspection based on airborne lidar is becoming more and more common. As the main data form of airborne lidar, point cloud data have become the third most important space-time resource data after vector map and image data.This principle uses the single-ended voltage and current to calculate the distribution of the norm of the voltage versus the distance derivative along the line to locate the fault point on the line. Through the analysis of the faulty line, it is found that the single-ended quantity is used to calculate the voltage distribution of the whole line, and if the result is behind the fault point, it is "false;" but the derivative of this "false" voltage distribution to the distance has a similar variation law to the derivative of the real voltage distribution to the distance. It not only provides accurate and effective three-dimensional (3D) information for power line safety monitoring but also has the potential and important value in the safe operation of transmission lines. Due to their low classification accuracy and efficiency, the traditional transmission line classification methods often have the phenomena of wrong classification and missing classification, so the traditional classification methods can not meet the needs of transmission line classification. The traditional transmission line maintenance implements a periodic maintenance system based on time. The improvement is achieved by using some statistical indicators to extract fault features from the current signal. The selected statistical indicators are simple and able to measure the relationship between random variables. Then a cumulative technique is used to amplify the corresponding fault features.

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Transmission line classification is an extremely complex problem, and a large number of point cloud data need to be collected and processed in the classification process, resulting in some difficulties in automatic classification of transmission lines [3]. The current flowing through the associated part of the overhead transmission line is detected. The data related to the detected current are stored and then wirelessly transmitted to the control unit. According to this detection device, it is possible to detect not only normal current and general fault current but also lightning current caused by lightning strikes, thereby detecting faulty parts of transmission lines. Figure 1 shows a denoising algorithm for laser ranging signal based on edge detection and filtering algorithm.

Melzer et al. first eliminated the ground points in the point cloud data, rasterized the point cloud data, and classified the power line points through Hough transform. This algorithm is the first method to extract power line points by Hough change and use catenary equation to model power line. However, this method also has some problems. For example, when the ground points are removed by pretreatment, the power line with vegetation in the lower part will be divided into non-power line points [4]. McLaughlin et al. divided point cloud data into three categories: power lines, vegetation, and land. First, the point cloud data are divided into several ellipsoid blocks, and the covariance matrix and point cloud individual values for each block are calculated so that each ellipsoid contains only the power line points of the same wire. Because power lines have one-dimensional linear properties, ellipsoidal points with only one large specific value are classified as power line points. The points of each wire are then installed and combined with the simplified catenary equation, and the power line is recreated in 3D. However, the power line extracted by this method contains a lot of noise. The power line noise constructed by the new power line noise model is not only the same as the real noise in the statistical law but also has a very high similarity in the time domain waveform, and the extracted power line points are discontinuous, and there are many leakage phenomena [5]. Jwa et al. used the cube to block the point cloud. First, they used the eigenvalue of covariance matrix, the peak coefficient of Hough transform space, and the point cloud density to roughly classify the power line points. Next, they determined the direction of the power lines of the candidate points and classified the power line points according to the F distribution of the point cloud data in the cube block [6]. Guan et al. in the case of point cloud data installed in urban vehicles, a number of filtering methods are first performed to remove road points and then to preserve power line points as much as possible and non-power line points, especially those without power. It is possible to remove the line points below the power line, complete the two-dimensional projection with Hugh's transformation, and detect the linear properties of power lines [7]. Kim et al. organized the data points as the basic units, derived some of the associated point cloud characteristics, and used a random forest classifier to classify the transmission line corridor point clouds [8]. Zhang et al. organized data with objects as basic units and also used Support Vector Machine (SVM) classifier to classify point cloud data in urban areas [9].

In this study, the edge detection filtering algorithm and airborne lidar technology are applied to the automatic classification of transmission lines; airborne lidar is an active remote sensing technology. In forestry applications, high-sampling density lidar can obtain the 3D structural characteristics of a single tree, and different data processing methods can be used to obtain individual tree parameters with different precisions. An automatic classification method for transmission lines based on edge detection filtering algorithm and airborne laser point cloud data is proposed, which improves the efficiency of automatic classification of transmission lines.

II. RESEARCH METHODS

The most important step for the data processing section of the overhead air power line test is to separate the tower and transmission line from the initial point cloud data and then detect the hazard points and model the data. The process of edge detection can be understood as the tracking process of edge points, and the particle filter algorithm is very effective for object tracking problems. The study of mining algorithms is based on Article 1 of the 2000s. The main idea is to segment the spatial properties according to the contextual connection of different categories in the transmission corridor phenomenon and then to use the method to accurately

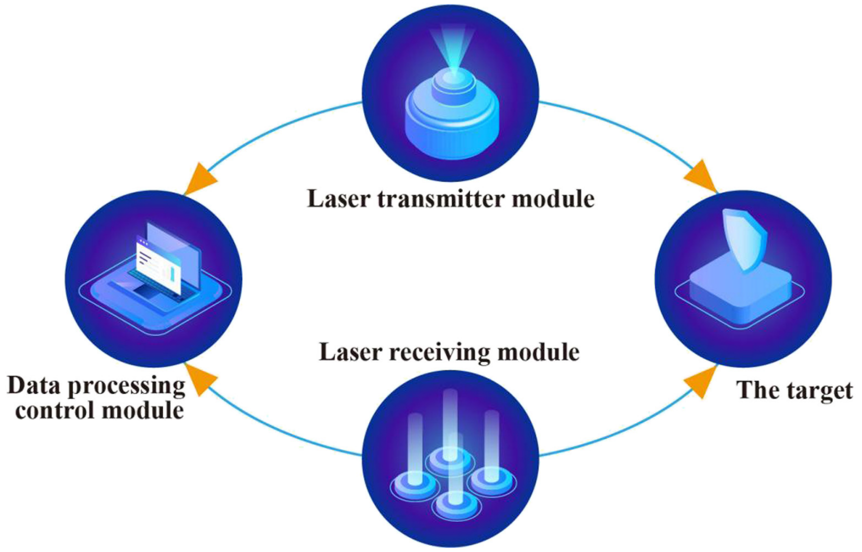

Fig. 1. A manufacturing technology of transmission line laser ranging signal denoising algorithm based on edge detection filtering algorithm.

determine the point cloud and adjust the decomposition function, power lines, or towers [10]. However, most methods only focus on the extraction of power lines and do not involve the location determination of towers, the accurate extraction of towers, and the classification of conductors and ground wires. First, the ground points are filtered by an edge detection filter, and the power facility point cloud is extracted by Euclidean clustering for the non-ground point cloud. Then the power facility point cloud is down-sampled to improve the operation speed. The tower center coordinates are located by means of suspension analysis and slicing, and then the tower center coordinates are used to roughly separate the power line and tower. After rough separation, the parameters of the spatial curve of a single power line are calculated using straight-line alignment and polynomial coupling methods. The study aims to develop an effective theory and technology for the accurate classification of transmission point clouds based on air slides [11].

A. Edge Detection and Filtering Algorithm

The 3D coordinates obtained by airborne lidar include not only the information reflected from the bare ground but also the information reflected from non-ground objects such as buildings, vegetation, roads, and vehicles. These non-ground points must be eliminated when extracting the digital ground elevation model, that is, the preprocessing of point cloud data. This process is similar to image noise filtering, so it is often called "filtering" [12].

The depth image of the laser point cloud can be provided in the form of grid image. Because the airborne laser obtains the elevation information of each laser foot point, the elevation of each pixel is strictly known. Depth image is a basic eigengraph, which can directly reflect the geometry of the visible surface of the scene. The depth image is encoded into brightness or chroma information and displayed, which can be interpreted and operated accordingly.

In the edge detection algorithm in this study, 2×2 pixel blocks are used for filtering. Assuming that $f(i,j)$ is a pixel of the input image and $g(i,j)$ is a pixel of the output image, the processing expressions for one of the pixels are as follows (1) to (3):

$$g(x)=\left[f(i,j)-f(i+1,j)\right]^2 \tag{1}$$

$$g(y)=\left[f(i+1,j)-f(i,j+1)^2\right] \tag{2}$$

$$g(x,y)=\sqrt{g(x)+g(y)} \tag{3}$$

B. Point Cloud Classification of Transmission Lines and Towers

Point cloud data are a kind of unstructured true 3D data. For cloud data in the transmission line corridor point, the spatial characteristics of the tower and the transmission line can be classified first by segmentation and then by identification. See Fig. 2, the method in this study mainly includes three steps: 1) extracting power facility point cloud by progressive morphological filtering and European clustering; 2) analysis of tower element and suspension center; and 3) fine extraction of power line and tower point cloud [13].

The purpose of transmission line point cloud classification is to distinguish power line and tower point clouds. Non-target clouds such as land and vegetation make up the majority of transmission corridor point cloud information. And the edge detection filtering algorithm is often used to distinguish the ground point cloud [14, 15].

1) Calculation of Tower Center Coordinates

Tower center cordinate calculation is given as follows: calculate the center coordinates of each high-voltage line tower based on the point cloud of each high-voltage line tower, take a certain point of a high-voltage line tower as the starting point and obtain the endpoint according to the set line of the high-voltage line tower number. The tower number of the high-voltage line tower where it is located and the tower number corresponding to each high-voltage line tower are obtained. The purpose of tower center coordinate calculation is to 1) roughly separate the power line and tower point cloud according to the tower center coordinate and 2) calculate the line direction L and rotate the line data around the Z axis to make the line direction parallel to the X axis.

1) Voxel down sampling
   It is necessary to traverse every point to analyze the suspension analysis, and the high data density of transmission line point cloud lead to large amount of calculation and high operation time. Therefore, the voxel down sampling of power facility point cloud_power will not change the overall characteristics of point cloud data. The main process is to regularize cloud_power into 3D grid $\{g_i\}$ according to the predetermined voxel size and to calculate the centroid point P_c in each g_i and use it to replace the other points in g_i, so that all points in each grid can be finally represented by one centroid point [16].
2) Suspension analysis
   The purpose of the suspension analysis is to roughly segment the tower point cloud from the sampled cloud_force and calculate the tower center coordinates. This process is based on the spatial distribution characteristics of the transmission lines and towers: the power line point cloud is hanging. The specific analysis process is given as follows: 1) take a point P as the center, take the cross arm width w_{cs} of the tower as the side length, and take the predetermined height h_c as the height to create the bounding box B_c; 2) take the upper surface of B_c as the bottom surface and h_{up} as the height to create bounding box B_{up} and take the lower surface of B_c as the top surface and h_d as the height to create bounding box B_d; and 3) query whether there are points in B_{up} and B_d, if d = 0 (|| = true), P ∈ cloud_ pylon_ downsampling, else, P∈cloud_ line_ downsampling, after the query, traverse the next point.
3) Calculation of tower center by slice method
   The suspension analysis can be used to obtain the tower point cloud_pylon_downsampling after downsampling. At this time, the slice method is used to calculate the tower center coordinates. The purpose is 1) to rotate the point cloud of single transmission line to make its trend parallel to the x-axis and 2) according to the coordinates of the tower center, the tower and power line are roughly separated from the power facility point cloud_ power sampled below. Since there may be missing vegetation at the upper end of the tower or connected vegetation at the bottom of the tower, the slice method is used to calculate the centroid of the point cloud at each layer of the tower, delete the centroid points with large deviation, and keep the average value of the centroid points as the center coordinates of the tower. The algorithm flow is shown in Fig. 3 [17, 18]. First, at least one solid color photo needs to be taken between two adjacent towers and stored in the photo sequence library according to the shooting time sequence; Second, establish the photo file folder corresponding to each tower, store the location

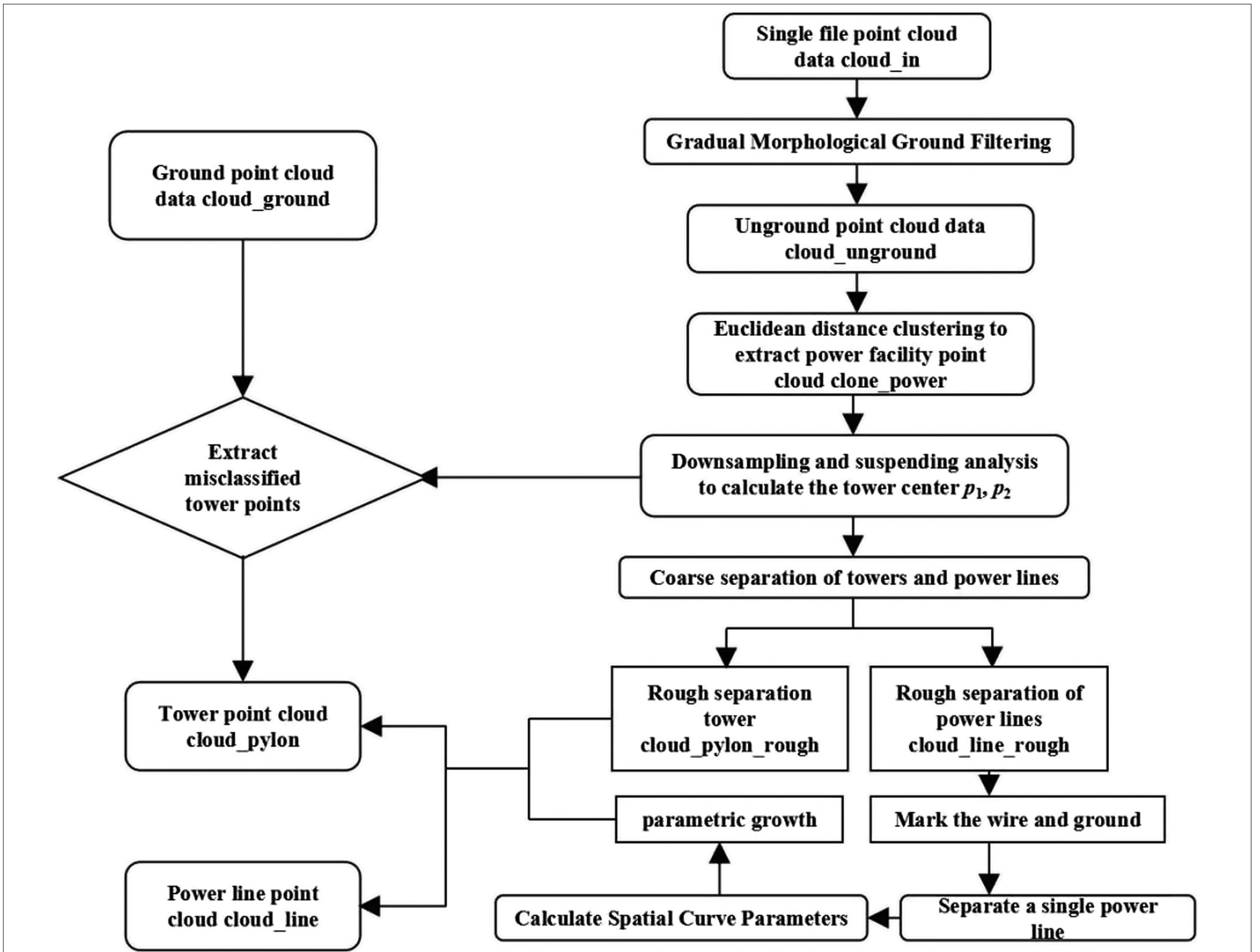

Fig. 2. Classification process of transmission line point cloud data.

coordinate information of each photo, and compare it with the coordinate information in the information database; Finally, it is necessary to identify the solid color photos in the photo sequence library and accurately determine the archive folder to which each photo belongs.

2) Fine Extraction of Power Lines and Towers

After the tower center coordinate {$Pylon_c$} is obtained through the suspension analysis, take $Pylon_c$ as the center and cross arm width w_{cs} as the diameter to make a circle C parallel to the horizontal plane. If the horizontal projection of a point p falls in C, the point is classified as tower cloud_ pylon_ rough, otherwise, it is classified as power line cloud_ line_ rough.

Incomplete power line point clouds can be obtained after roughly separating the coordinates of the line and the center of the tower.

1) Fine power line extraction based on line and parabola fitting
In natural circumstances, the power line can be regarded as a suspension line suspended on the tower at both ends, a straight line model on the horizontal plane and a catenary model on the vertical plane. Because the catenary equation is complex, it can be approximately expressed by parabola. Therefore, the fitting process can be divided into two steps: 1) straight-line fitting and 2) parabola fitting [19].

Take the line L between tower center coordinates obtained in the previous section as the direction of single gear transmission line, and calculate the included angle θ between L and x axis. Then rotate the point cloud data around the z-axis θ degrees so that the direction of the point cloud is parallel to the x-axis. Then, the power line is projected to the o–xy plane, and the curve parameters (k^*, b^*, A^*, B^*, C^*) are obtained by least square fitting for the parabolic model of equation (5).

$$y = kx + b \tag{4}$$

$$z = Ax^2 + Bx + C \tag{5}$$

After obtaining the linear parabola model parameters (k^*, b^*, A^*, B^*, C^*) of a single power line, perform this operation on each power line to finely separate the power line from the tower [20].

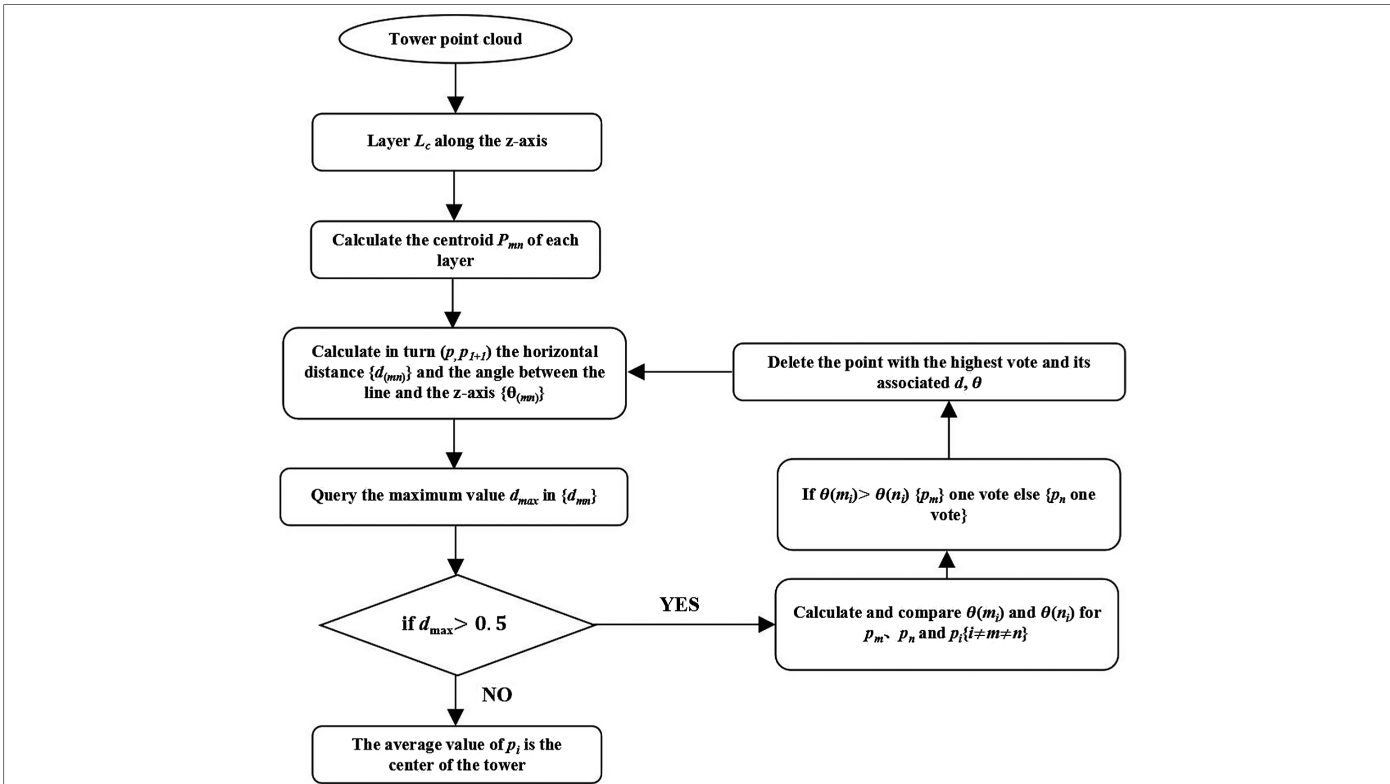

Fig. 3. Calculation of tower center position.

2) Ground wire and wire marking
The power line of high-voltage transmission line is divided into two grounding wires and several transmission conductors. For general high-voltage lines, there are two main differences between grounding wires and conductors: 1) conductors are multi split wires, 500 kV high-voltage lines are usually 4-split wires, and a single ground wire has no split wires and 2) the ground wire is located at the top of the line and the conductor is located below the line. According to these two differences, a marking method based on elevation features and residual error with spatial parameter model is proposed [21].
The marking process is given below:
(1) Calculate the residual Δy_j of each point $P_j(x_j,y_j,z_j)$ in the y direction with the straight line model $f_1 = k_i^* x + b_i^*$ and the residual Δz_j in the z direction with the parabolic model $f_2 = A_i^* x^2 + B_i^* x + C_i^*$ from PL_i and calculate the residual v_j of point P_j and the power line model with (6):

$$v_j = \sqrt{\Delta y_j^{\,2} + \Delta z_j^{\,2}} \tag{6}$$

(2) Use formula (7) to calculate the mean square error δ_i of single power line PL_i according to residual {v_j}. After the calculation of n power lines, the two power lines with the smallest δ_i are ground wires and the others are marked as conductors [22].

$$\delta_i = \sqrt{\frac{vv^T}{n}} \tag{7}$$

3) Tower fine extraction
The tower fine extraction is given as follows: take the tower center plane coordinate $Pylon_c(x,y)$ obtained in the above section as the center, take the tower base width as the side length, make a rectangle R parallel to the horizontal plane, extract the points in the cloud_ ground where the horizontal projection falls in R as the candidate point cloud_ candidate, and slice the cloud_ candidate as the floor height. Because there is a large gap between the ground and the tower point cloud density, the point cloud density of each layer is counted, and the layer with the highest density is classified as the ground point, and other points are classified as the tower point. So far, the whole classification process has been completed [23, 24].

III. RESULT ANALYSIS

A. Experimental Results

This study uses C++ language and Point Cloud Library (PCL) library to realize and verify the extraction accuracy and efficiency of the algorithm. Two sets of data are used in the experiment. The first set of data is a 500 kV high-voltage transmission line in Jiangsu Province. There is basically no requirement for the amount of external information in the search. The basis of the particle moving in the high-dimensional space comes from the fitness function value. It is an adaptive intelligent optimization algorithm. For various optimization problems, there are no strong restrictions on the objective function such as continuity and derivation, and it shows good versatility, and the strategy of distributed parallel search is adopted in the optimization process.The terrain is relatively flat, but the point cloud density is low, which is 86 pts/m^2. The second set of data is a 500 kV high-voltage transmission line in Shandong Province, with obvious topographic relief and low point cloud density, which is 89 pts/m^2. The adaptability of edge detection and filtering is strong, and it also has a good effect on the data with large topographic relief. The coarse

TABLE I. COMPARISON OF TOWER CENTER COORDINATES(M)

	X Coordinate			Y Coordinate			
Tower Number	**Manual**	**Algorithm**	**Error**	**Manual**	**Algorithm**	**Error**	**Horizontal Error**
1	765256.544	765255.769	0.577	3741225.364	3741225.002	0.363	0.680
2	765361.497	765361.581	0.785	3740855.995	3740855.021	0.973	1.250
3	765483.109	765482.502	0.909	3740426.875	3740427.002	0.325	0.964
4	765589.467	765589.832	0.064	3740052.577	3740052.317	0.027	0.267
5	765723.598	765723.193	0.706	3739579.222	3739579.964	0.747	1.025
6	765826.732	765826.665	0.633	3739218.298	3739218.682	0.391	0.744
7	765972.124	765972.021	0.103	3738704.736	3738703.724	1.015	1.020
8	766103.186	766103.735	0.549	3738243.184	3738243.591	0.402	0.680
9	766222.266	766222.697	0.631	3737823.529	3737823.935	0.406	0.751
average			0.550			0.516	0.820

separation process of power line and tower is based on the center coordinates of the tower, and some power line point clouds connected with the tower are mistakenly divided into tower points [25].

B. Result Analysis

The feasibility and accuracy of this algorithm are evaluated by comparing it with the manual processing results, mainly from the two aspects of tower center position and classification accuracy. For the tower center plane coordinates, the plane center positions of nine towers are obtained by using the slicing algorithm in this study. The mining error was calculated based on the results of manual mining. The results of the comparison are shown in Table I and Fig. 4. The average error in the direction is 0.55 m, the average error in the y direction is 0.54 m, and the average horizontal error is 0.82 m. Therefore, the method of determining the location of the tower in this document fully meets the requirements of the transmission line inspection.

For the classification accuracy of power line and tower, select the data of seven files in data 1 and data 2, evaluate the classification accuracy by counting its precision V_{pre} and recall V_{rec}, and compare it with the most commonly used power line inspection classification software LiPowerLine on the market.

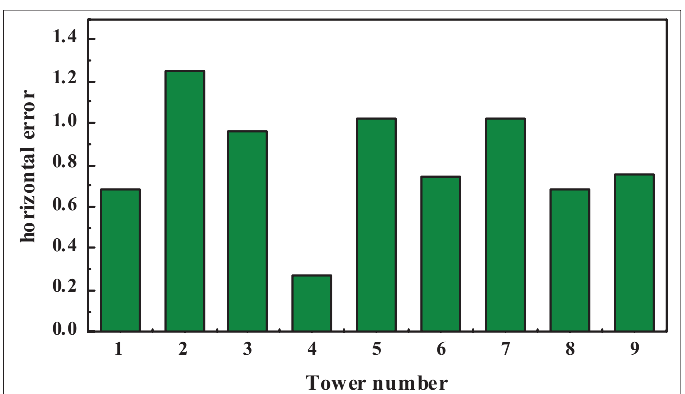

Fig. 4. Horizontal error results.

The calculation formulas of precision and recall are given in (8) and (9):

$$V_{pre} = \frac{TP}{TP + FP} \tag{8}$$

$$V_{rec} = \frac{TP}{TP + FN} \tag{9}$$

Positive examples are the number of positive examples correctly classified in formula A. Negative examples are the number of positive instances that are incorrectly classified.

The manual classification results are taken as the real value and compared with the algorithm results and LiPowerLine results in this study. The algorithm analysis results in this study are shown in Table II. For the tower, the precision rate (99.74%) is high and the recall rate (98.26%) is the lowest. The main reason is that when the power line is finely separated from the tower, some conductors connected with the power line are wrongly divided into power line points due to the setting of model growth threshold. The secondary aspect is the tower base part. Due to the problem of setting ground filtering parameters, some tower base point clouds will be classified as ground points. During the fine extraction of towers, due to the problem of layered height, a small part of towers will be divided into ground points or a small part of ground points will be divided into towers.

TABLE II. CLASSIFICATION ACCURACY OF THIS ALGORITHM

Category	**Tower Point**	**Traverse Point**	**Ground Point**	**Other Points**	**Recall Rate**
Tower point	183637	676	1594	975	98.24%
Traverse point	0	86221	0	0	100%
Ground point	130	0	67312	0	99.81%
Other points	340	0	0		
Recall rate	99.73%	99.22%	97.66%		

TABLE III. CLASSIFICATION ACCURACY OF LIPOWERLINE

Category	Tower Point	Traverse Point	Ground Point	Other Points	Recall Rate
Tower point	181302	6694	1204	1477	95.07%
Traverse point	0	83187	0	0	100%
Ground point	1264	0	60869	0	97.97%
Other points	1235	0	0		
Recall rate	98.65%	92.56%	98.05%		

For the conductor and ground wire, because the error mainly comes from the part connected to the tower, its recall and precision are high. The reason why the ground wire accuracy is lower than the conductor accuracy is that the conductor is generally connected with the insulator. The growth of the model will only cause a small part of the insulator to be divided into conductor points, while the ground wire is directly connected with the main body of the tower. Therefore, it is easy to divide the point cloud at the end of the tower into ground wires.

The classification results of the algorithm in this study are significantly better than LiPowerLine software in terms of recall and precision (see Table III), especially in terms of precision of traverse points. Therefore, the algorithm in this study has certain practical value in improving the processing accuracy of patrol data.

IV. CONCLUSION

In this study, the spatial distribution characteristics of power line and tower point cloud data in transmission line corridor are obtained after edge detection and filtering algorithm processing. The accuracy of the output probability is determined according to the size of the track random number to update the statistical information of the state category. After obtaining the observation probability and initial probability of fault features, the cluster center update rule is implemented. The Hadoop cluster cloud computing prototype system is built on the open-source cloud computing platform. The data acquisition and algorithm implementation are carried out under the framework and HBase power grid system database. The simulation results show that the algorithm has good application performance in data clustering and fault detection. A segmentation method is proposed for the classification and extraction of power lines and towers, which is verified by the airborne lidar transmission line point cloud data collected by unmanned helicopters. Taking the manual classification results as the true value for analysis, the accuracy of this algorithm in tower positioning and conductor, ground wire, and tower extraction is verified. The method is applied to a cloud server, and the method includes: acquiring point cloud data to be classified in a target area; inputting the point cloud data into a pre-established classifier, and outputting an initial classification result corresponding to the point cloud data, modifying the wrongly classified point cloud data in the initial classification result, removing the noise points, and getting the final tower and power line classification results.The results fully meet the needs of transmission line corridor inspection and have high practical value. In the future, new passive sensing technology will be applied on transmission lines, that is, by applying network topology, lithium-iron batteries, and surface acoustic wave sensors on transmission lines to solve the problems of unstable operation, poor operation reliability, etc., of existing transmission line wire temperature monitoring systems. The problem of easy interruption of operation and high cost of operation and maintenance.

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