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STUDY OF WIRE SEGMENTING ALGORITHM OF SUBSTATION EQUIPMENT BASED ON 3D POINT CLOUD

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Abstract. *In this paper, a cone search method is proposed to segment the wire from substation equipment based on three-dimensional (3D) point cloud. On the one hand, the segmentation of the wire which connects to substation equipment can improve the recognition rate of the point cloud of substation equipment. On the other hand, it can reduce operation workload and improve the efficiency of the intelligent identification of substation equipment. In the process of wire segmentation, first, the position of substation device is located by rotating, and two endpoints of the wire are found. Second, other endpoints of the wire are found by using K-means clustering algorithm and the nearest neighborhood search algorithm. Then use linear fitting based on three-dimensional point cloud to search the data of wire and solve the problem of defective wire points. Finally, using the cone search to confine search direction, find out the wire points and remove it. The key findings of this study include the following. (a) A cone search method proposed to divide wires from substation equipment in 3D point cloud is effective, and (b) using linear fitting based on three-dimensional point cloud can solve the problem of defective wire points. Experiments show that using the method can remove the wire well in substation equipment.*
Keywords: Wire segmenting, K-means clustering algorithm, Linear fitting, Substation equipment, Cone search method

1. **Introduction.** In recent years, intelligent substations have emerged and been widely used [1]. The purpose of segmenting wire which connects to a substation device is to improve the identification rate of the device, to achieve the reconstruction of substation equipment. It is also a crucial way to promote the development of intelligent substation. In the process of automatic segmentation, the existence of wire has a great impact on the feature extraction of the device, which decreases the identification rate of the device. Therefore, it is very meaningful to segment wire from substation equipment using intelligent algorithm. On the one hand, segmenting wire can improve the identification rate of the equipment. On the other hand, it can reduce the workload of manual operation and improve the efficiency of the intelligent identification of substation equipment.

Generally, segmentation methods can be grouped into four major categories, which are K-means clustering segmentation, edge-based segmentation, region-based segmentation and color-based segmentation, separately [2]. Because there is no any literature studying on wire segmenting algorithm of substation equipment point cloud, we can only refer to the segmentation algorithms of other fields to provide ideas for wire segmentation. The authors proposed a method to combine deep learning and regional growth algorithms to

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segment individual maize from 3D point cloud. The method uses deep learning to detect the stem of individual maize [3]. Because the length and the position of wire are very different between different devices, this method cannot find the position of a wire accurately. The authors propose a voxel and probabilistic model-based method for 3D point cloud segmentation [4]. Because wires are connected to substation equipment, it will cause the data of wire failing to be segmented completely. The authors present a method for improving the quality of automatic single fallen tree stem segmentation in 3D point cloud data by applying a specialized constrained conditional random field [5]. Because the position of fallen tree stem is fixation, and the wire position is not fixation, this method cannot find the position of wire accurately. Chen et al. proposed an improved random sample consensus (RANSAC) algorithm to segment rooftop primitives, and the algorithm maintains topological consistency among primitives and avoids under- and over-segmentation [6]. Zhou et al. proposed an efficient two-step segmentation method for large-scale 3D point cloud data [7], but this method has no good segmentation effect on unordered point cloud data. The authors use binarization image to divide wires from multiple aerial images, according to the different pixel values of the wires and the surrounding environment [8], and Huang et al. proposed an end-to-end full-convolutional neural network model for power line detection on mobile terminals to perform semantic segmentation of wires [9], but these methods are ways for flat image, and not suitable for 3D point cloud data.

Point cloud of substation device has characteristics that the amount of data is huge, and the shape of point cloud is irregular, and subsidiary facilities, such as wires, and base, are integrated with the main body of substation device. At present, there is little research on the algorithm of segmenting wire from substation equipment. The above methods are difficult to be directly applied to segmenting the wire. In order to solve the above problems, this paper proposes a new method to segment wire from substation equipment. This method is based on the characteristics of the ancillary wire of substation equipment, which include the following. 1) The wire is straight; 2) the curvature of the contour of the wire does not mutate; 3) the diameter of the wire does not mutate. As far as the main technical contributions of this paper are concerned, they can be summarized as follows.

1) Propose a cone search method to realize the segmentation of wire from substation equipment in 3D point cloud.

2) Using linear fitting based on three-dimensional point cloud can solve the problem of defective wire points rapidly. It is beneficial for searching electrical wires correctly.

3) Experimental result shows that the wire-search algorithm can find the wire endpoints accurately and segment the wire completely, which will contribute to improving the identification rate of the equipment.

4) The method will play an important role in three-dimensional identification and reconstruction of substation equipment.

2. **Total Frame.** This paper mainly studies substation equipment wire segmenting algorithm. Specifically, the implementation process of the algorithm is expressed as follows. First, use octree method to denoise point cloud data of substation device. Second, change the direction of the device by using rotating. The purpose of rotation is to make the wire connected to the device lie in x direction as much as possible. Two possible wire endpoints, which can be confirmed by the characteristic of the wire endpoints in subsequent step, can be found in this step. Third, using K-means clustering algorithm and the nearest neighborhood search algorithm can find the position of other wire endpoints. Fourth, judge the possible wire endpoints are real wire endpoints according to the characteristic of the wire endpoints. Fifth, using linear fitting based on three-dimensional point cloud to search the data of wire and solve the problem of defective wire points. Finally, use

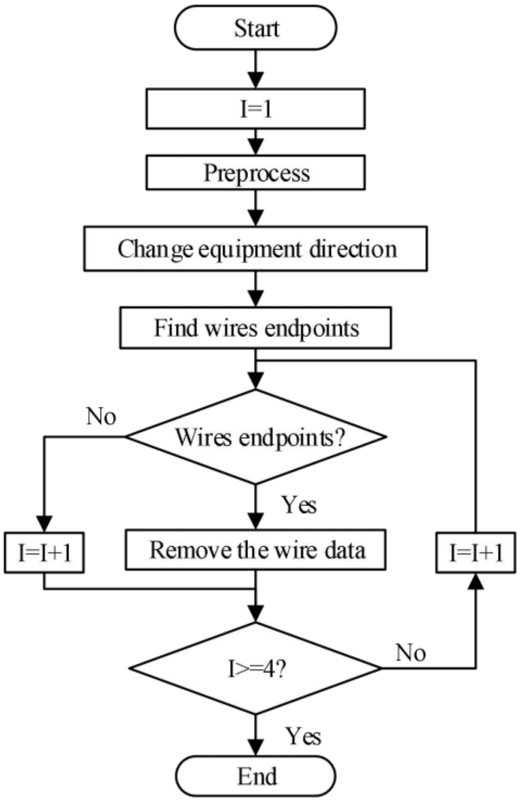


Figure 1. Flow chart of total algorithm

cone search algorithm to confine the search direction, and find out the data of wire and remove the wire points. The flow chart of the total algorithm frame is shown in Figure 1, where I is the number of the wire endpoints.

It is found that the number of wire endpoints is no more than four by testing some substation devices. Therefore, if $I \geq 4$, the segmenting algorithm will skip loop and stop. The location of wire is shown in Figure 2. Specifically, steps of the wire segmenting algorithm are written as follows.

Step 1: Two possible endpoints of the wire can be found by changing the direction of a substation device.

Step 2: Use K-means clustering algorithm and the nearest neighborhood search algorithm to find the other two possible endpoints of the wire.

Step 3: Judge the endpoints are wire endpoints on the characteristic of the wire endpoints.

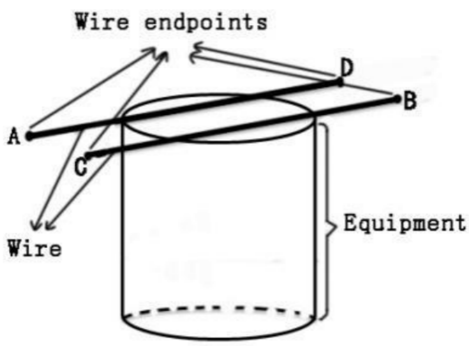


Figure 2. The location of wire and wire endpoints

Step 4: Use linear fitting to search the data of wire and solve the problem of defective wire points.

Step 5: Using cone search algorithm to confine the search direction, the paper finds the wire points and removes it.

3. Equipment Wire Segmenting. One highly successful and widely available technology, which is accurate, contactless and fast, is laser line scanning technology [10,11]. In this paper, three-dimensional point cloud data of substation equipment acquired by 3D laser scanner is provided by Henan Tenglong Information Engineering Co., Ltd. By observing and testing the substation equipment, it is found that the number of some wire is four (with four wire endpoints, shown in subfigures (a), (b) of Figure 3), and that of other wire is two (with two endpoints, shown in subfigures (c), (d) of Figure 3), and the positions of the wire are all above the substation equipment. In order to improve segmenting efficiency, the range of searching wire is limited in the top half part of substation device. Figure 3 shows several typical forms of substation equipment wire.

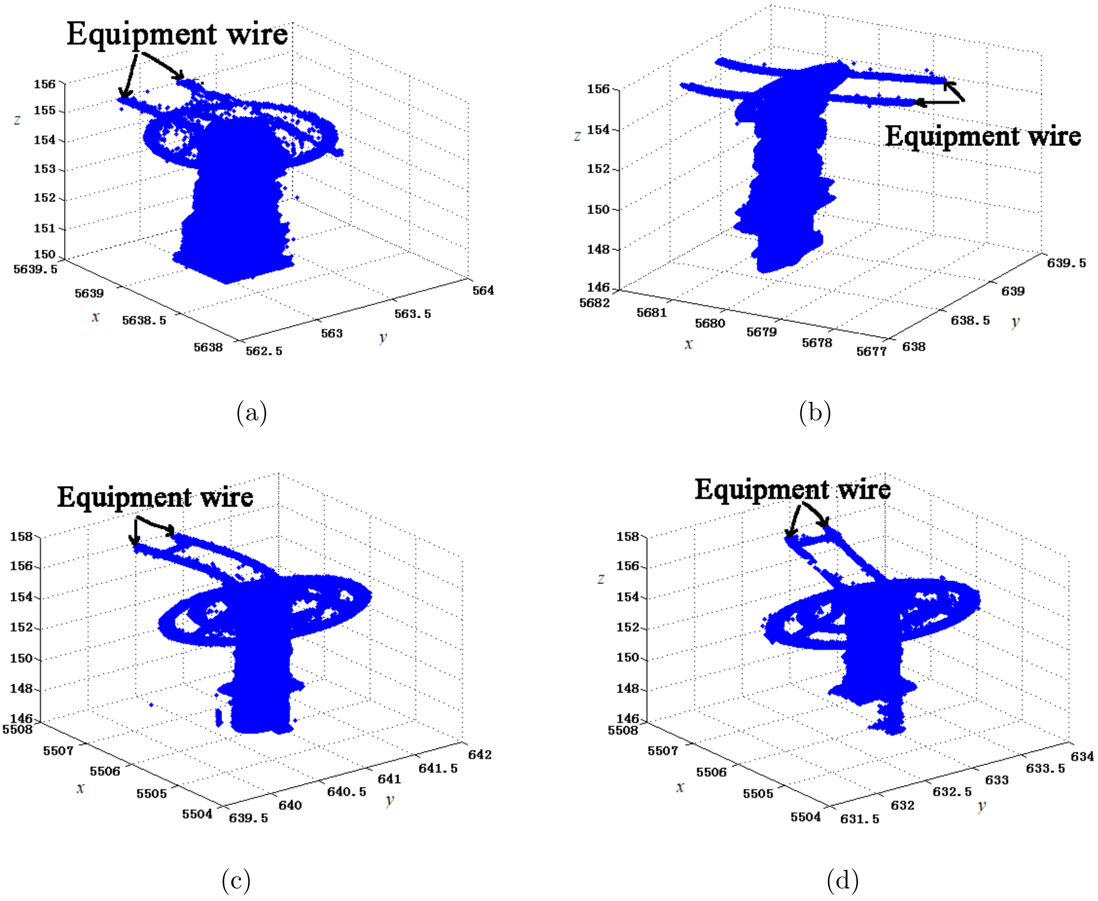


FIGURE 3. Forms of several substation equipment wire

This paper focuses on removing substation equipment wire, in order to eliminate the impact of the wire on the equipment body.

3.1. Preprocessing. The preprocessing of substation equipment is de-noising. Because the data of wire is less than that of equipment body, if the substation equipment's point cloud data is simplified, there will be less point cloud data of the wire, causing the wire points not to be searched accurately. Therefore, the point cloud data of substation

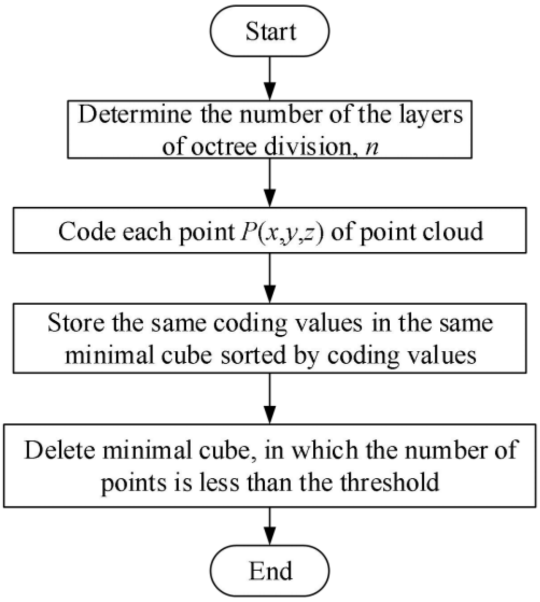


FIGURE 4. Flow chart of de-noising point cloud

equipment is only denoised. This paper uses octree method to denoise point cloud data of substation equipment [12,13], and the point cloud de-noising process is shown as Figure 4.

3.2. **Changing the direction of equipment.** The purpose of changing the direction of equipment is to determine the general direction of wire, so that the wire tries to lie along the direction of the x-axis and facilitate searching the wire endpoints. Specifically, the process of changing the direction of equipment is expressed as follows. Continually rotate the equipment on the z-axis from 0 to 180 degrees, and calculate the maximum distance between the left most point and the rightmost point along the x-axis direction, and find out the positions of two possible wire endpoints, namely, changing the direction of equipment is completed. In practice, most equipment's wire extrudes equipment body if the equipment is projected on x-y plane and few devices' wire is inside equipment body. If the equipment's wire extrudes equipment body, at less one of the above two possible wire endpoints is the wire endpoint. If the equipment's wire is inside equipment body, using the following method can judge the endpoints are not wire endpoints, and searching wire data will not start from these endpoints. Figure 5 shows the wires are outside and inside equipment body.

Suppose the top half part of substation equipment's matrix is $\boldsymbol{S}$ and rotation angle is θ. Therefore, the rotation matrix, $\boldsymbol{R}$, and equipment's matrix after rotation, $\boldsymbol{Z}$, can be

Equipment's wire is outside equipment body Equipment's wire is inside equipment body

FIGURE 5. Relationship between wires and equipment

shown as

$$\boldsymbol{R} = \begin{bmatrix} \cos\theta & -\sin\theta & 0 \\ \sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{1}$$

$$\boldsymbol{Z} = \boldsymbol{S} * \boldsymbol{R} \tag{2}$$

3.3. **Searching wire endpoints.** The positions of two endpoints of the wire can be got after changing the equipment's direction. Then the device is projected into x-o-y plane, and forms a two-dimensional scatter. Use K-means clustering algorithm to find the other two endpoints of the wire. Figure 6 shows the projection of device CP_C_3 on x-o-y plane.

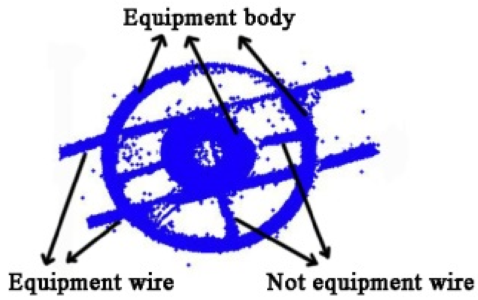


FIGURE 6. Projection of equipment on x-o-y plane

In Figure 7, the positions of two endpoints, which are the left most point and the rightmost point along the x-axis direction and marked as A and B, can be got after changing the equipment's direction. The line between A and B is set as x-axis. The specific process of searching the other two endpoints is expressed as follows.

1) The line segment $L1$ which passes through point A is the vertical of line segment AB, and $L2$ is parallel to $L1$. The distance between $L1$ and $L2$ is the wire's diameter, d, and the two-dimensional scatter between the two line segments is Q, shown in Figure 7. By detecting how many regions Q can be divided into, how many wires Q passed can be got. The steps of detecting Q are expressed as follows. In the scatter Q, shown in Figure 8, if the distance between point (m) and point (n) is greater than $d1/2$, where $d1$ is the distance between two wire, point (m) and point (n) are regarded as one group. Traverse all points of Q and we get all groups. If the number of the groups is more than 5, it is considered that Q passes through two regions. Otherwise, Q passes through one region.

2) If Q passes through one region, as shown in Figure 7, it is necessary to parallelly move the lines $L1$ and $L2$ to right for one time, and the distance to move is $d/3$. For

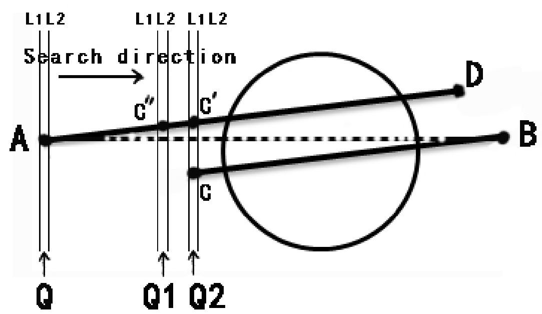


FIGURE 7. The process of searching the wire endpoints

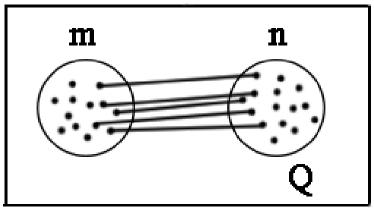


Figure 8. Determining the search direction

each new region produced by one time of moving, the above paragraph method is used to detect how many regions Q passes through. $L1$ and $L2$ do not stop moving until region Q passes through two regions. At this time, Q is marked as $Q2$, and the region produced by the previous time moving is marked as $Q1$. Then use K-means clustering algorithm to analyze the regions $Q2$ and $Q1$, the number of clustering centers is set to be two and one, separately. Using K-means clustering algorithm can get corresponding clustering centers, marked as (C, C') and C'', separately. Then calculate the Euclidean distances between C'' and other two points (C, C'), separately. The distance between C'' and C is $d2$, and the distance between C'' and C' is $d3$. If the distances $d2$ and $d3$ meet $d2 > d3$, the point C is regarded as the wire endpoint; otherwise, the point C' is regarded as the wire endpoint. Figure 7 shows the process of searching wire endpoints.

If region Q passes through two regions, it is necessary to parallelly move the lines $L1$ and $L2$ to left for one time. $L1$ and $L2$ do not stop moving until region Q passes through one region. Using K-means clustering algorithm can also search the wire endpoint. The process of searching is the same as the above process.

3) Similarly, let us build two vertical lines of line segment AB. One is through point B, and the distance between these two lines is d. Use K-means clustering algorithm to find out the wire other endpoint D. The specific K-means clustering algorithm is expressed as follows [14].

Step 1: K points are randomly selected from the two-dimensional region, Q, as initial cluster centers.

Step 2: Calculate the Euclidean distances between each point of Q and the cluster centers, separately. It is easy to classify the sample points to each cluster according to the principle of the nearest distance.

Step 3: According to the initial classification obtained in Step 2, the mean value of each category is calculated to update the corresponding clustering center.

Step 4: Repeat Step 2 and Step 3 until the new clustering centers reach threshold.

The above algorithm can search four endpoints in two-dimensional projection plane. By using projection relationship, the four corresponding three-dimensional points can be found. However, it is not certain whether the four endpoints are the wire's endpoints; the further detection of endpoints is needed. In this paper, the number of points around each endpoint, the distance between two endpoints on the same side, the projected area around the endpoint, and the height of the endpoint are all used to judge whether or not they belong to the endpoints of the wire.

3.4. **Searching equipment's wire.** Linear fitting based on three-dimensional point cloud, and the nearest neighborhood search algorithm, are used to find wire points. Use cone search to confine the direction of searching wire. Figure 12 shows the entire searching process from the wire endpoint A.

First, starting from the endpoint A, centre of a sphere, the searching process is performed in 360° range, with r_1 as the ex-sphere radius and r_2 as the inner sphere radius

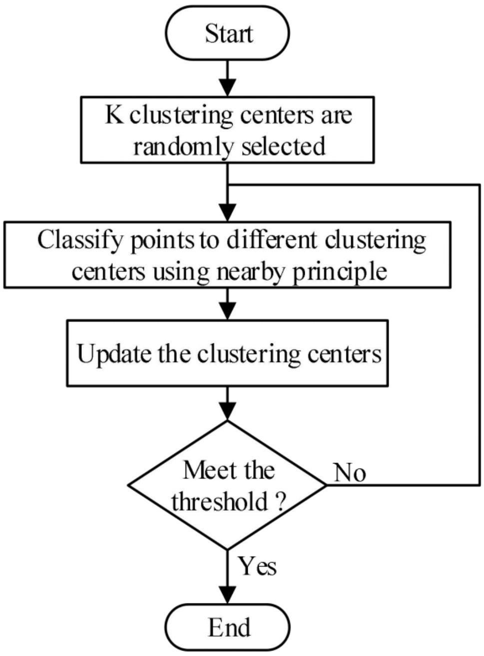


FIGURE 9. Flow chart of K-means clustering algorithm

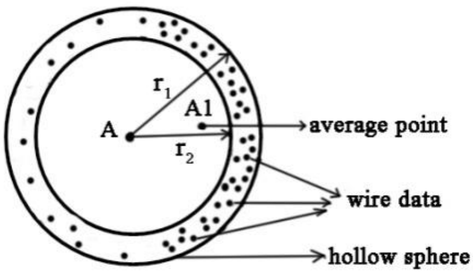


FIGURE 10. A hollow sphere in searching process

(where $r_1 > r_2$), which leads to form a hollow sphere, shown in Figure 10. The average point of the points in the hollow sphere, marked as $A1$, can be obtained by K-means clustering algorithm, and the first time of searching is finished.

In order to void backward searching, which will affect the second time of searching, the point cloud data in inner sphere, whose radius is r_2, will be removed. Then $A1$ point is set as a new starting point, the searching process is performed in 360° range to get a new hollow sphere, the same as the above operation. The average point $A2$ of the second time of searching is got by K-means clustering algorithm, and the next average point $A3$ is obtained by the same way.

The ranges of the first three times of searching are all 360°, so there is no directionality for searching. In the following searching process, the searching direction will be confined, so that the searching direction is consistent with the direction of the wire. For the above three times of searching, the four points $(A, A1, A2, A3)$ were spatially fitted to form a vector, $\overrightarrow{\boldsymbol{PQ}}$, as the main direction. In the next time of searching, $A3$ point is set as a starting point with r_1 as the ex-sphere radius and r_2 as the inner sphere radius, to search within 360° range. The above searching can form a new hollow sphere, whose points are regarded as a new point cloud, C. Suppose M is a perpendicular foot where A is perpendicular to vector $\overrightarrow{\boldsymbol{PQ}}$, and N is a perpendicular foot where $A3$ is perpendicular to vector $\overrightarrow{\boldsymbol{PQ}}$. Many triangles can be formed by point M, point N and every point C_i of point cloud C, and the following formulas can be calculated:

$$\theta' = \angle MNC_i \tag{3}$$

$$\theta = 180^\circ - \theta' \tag{4}$$

By limiting the size of θ, some points that do not satisfy the size condition will be discarded. In this way, this paper can confine the direction of searching wire. The searching direction will be changed every time, just like a cone, as shown in Figure 11. The point whose θ meets $\theta > 85^\circ$ will be discarded, and a clustering center $A4$ can be got from the rest points. The determining process of parameter θ is given in Section 4.2.

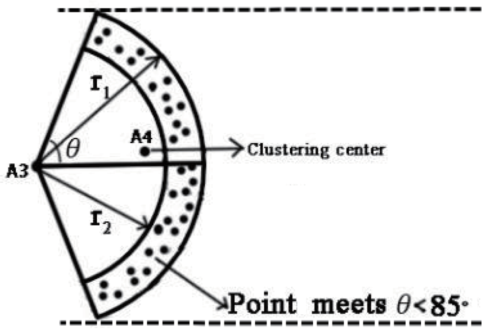


FIGURE 11. A cone searching direction

The searching process from $A4$ to $A5$ needs five points $(A, A1, A2, A3, A4)$, and the rest is the same way as $A3$ to $A4$. In the next time of searching, it needs only five points to be linear fitted, that is, the oldest point is discarded, and the newest clustering center point is added to form a new five points group $(A1, A2, A3, A4, A5)$. Search wire points until the number of points in the hollow sphere is zero. In order to void the impact of defective wire points, if 15 consecutive cases occur, in which the number of the points in the hollow sphere is zero, stop the process of search, which leads to completing the process of wire searching from endpoint A. Remove the data searched and achieve the purpose of segmenting wire. Figure 12 shows the process of searching wire points from endpoint A. The searching processes from the other three endpoints are the same as that from A.

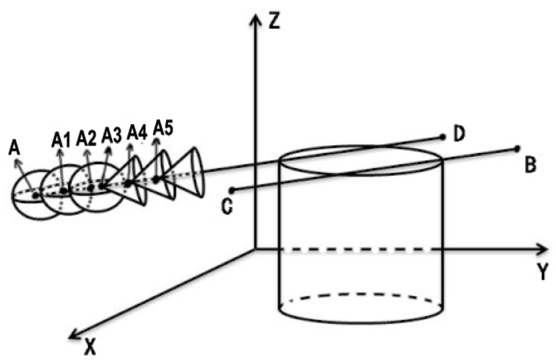


FIGURE 12. Process of searching wire points from A

3.5. **Linear fitting based on the three-dimensional point cloud.** In this paper, the least squares method [15] is used to achieve linear fitting based on three-dimensional point cloud. Suppose the coordinate of a space point is (x_i, y_i, z_i), the projection coordinates of the x-o-y and y-o-z planes are (x_i, z_i) and (y_i, z_i), respectively. All points of point cloud are projected on x-o-y and y-o-z planes. By using all projected points of each plane, one line is fitted in the corresponding plane, respectively. Suppose the line of x-o-y plane is $z = a_1 + b_1x$ and the line of y-o-z plane is $z = a_2 + b_2y$. Obviously these two lines are also the projections of the line that need to be fitted on the corresponding plane, and the lines $z = a_1 + b_1x$ and $z = a_2 + b_2y$ in two-dimensional plane are two planes in the three-dimensional space. Therefore, the intersection of these two planes is the required fitted line in the three-dimensional space.

The equations of the line fitted by the least squares method in x-o-z plane are written as follows [16].

$$\begin{cases} na_1 + b_1 \sum_{i=1}^{n} x_i = \sum_{i=1}^{n} z_i \\ a_1 \sum_{i=1}^{n} x_i + b_1 \sum_{i=1}^{n} x_i^2 = \sum_{i=1}^{n} x_i z_i \end{cases} \tag{5}$$

$$\begin{cases} a_1 = \dfrac{\sum_{i=1}^{n} z_i \sum_{i=1}^{n} x_i^2 - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} x_i z_i}{n \sum_{i=1}^{n} x_i^2 - \left(\sum_{i=1}^{n} x_i\right)^2} \\ b_1 = \dfrac{n \sum_{i=1}^{n} x_i z_i - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} z_i}{n \sum_{i=1}^{n} x_i^2 - \left(\sum_{i=1}^{n} x_i\right)^2} \end{cases} \tag{6}$$

where n is the number of points in point cloud.

The equations of the line can be reduced from Equations (5) and (6).

$$z = \frac{\sum_{i=1}^{n} z_i \sum_{i=1}^{n} x_i^2 - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} x_i z_i}{n \sum_{i=1}^{n} x_i^2 - \left(\sum_{i=1}^{n} x_i\right)^2} + \frac{n \sum_{i=1}^{n} x_i z_i - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} z_i}{n \sum_{i=1}^{n} x_i^2 - \left(\sum_{i=1}^{n} x_i\right)^2} x \tag{7}$$

In the same way, the equation of line fitted on y-o-z is

$$z = \frac{\sum_{i=1}^{n} z_i \sum_{i=1}^{n} y_i^2 - \sum_{i=1}^{n} y_i \sum_{i=1}^{n} y_i z_i}{n \sum_{i=1}^{n} y_i^2 - \left(\sum_{i=1}^{n} y_i\right)^2} + \frac{n \sum_{i=1}^{n} y_i z_i - \sum_{i=1}^{n} y_i \sum_{i=1}^{n} z_i}{n \sum_{i=1}^{n} y_i^2 - \left(\sum_{i=1}^{n} y_i\right)^2} y \tag{8}$$

Therefore, the required linear equation in three-dimensional space is

$$\begin{cases} z = a_1 + b_1 x \\ z = a_2 + b_2 y \end{cases} \tag{9}$$

3.6. **Solving the defective wire points.** If the number of points within the hollow sphere is zero, the first consideration is the problem of defective wire points, but not the completion of searching wire points. The solution is to use a linear equation of the 3D space which is formed by clustering center points searched previously, to get a fitted line segment. Then extend the fitted line segment forward by a fixed step length, λ, in order to get the next clustering center point, M. Figure 13 shows the case of defective wire point.

In Figure 13, the line segments AB and CD are substation device wire, and the line segment BC is the defective part of the wire AD. In the process of searching, the coordinates of A and B are known. The method to solve the problem of defective wire points is to use the coordinates of A and B, the step length, λ, to calculate the coordinate of M. Therefore, the process of searching extends the fitted line segment AB forward to

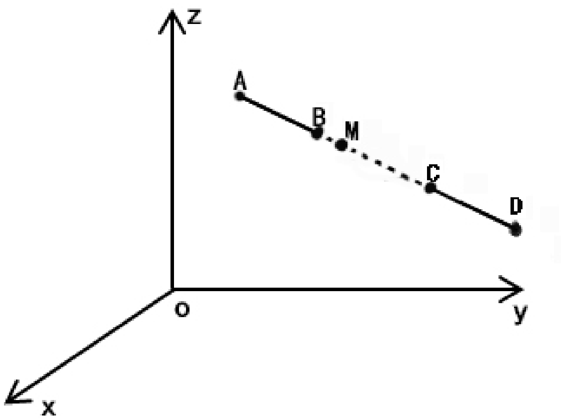


FIGURE 13. The case of the defective wire points

the point M, skips the defective data of BM and solves the problem of the defective wire points. The following formulas show the process of calculating the coordinate of point M.

In Figure 13, vectors $\overrightarrow{\boldsymbol{AM}}$ and $\overrightarrow{\boldsymbol{BM}}$ can be expressed as

$$\overrightarrow{\boldsymbol{AM}} = \overrightarrow{\boldsymbol{OM}} - \overrightarrow{\boldsymbol{OA}} \tag{10}$$

$$\overrightarrow{\boldsymbol{BM}} = \overrightarrow{\boldsymbol{OM}} - \overrightarrow{\boldsymbol{OB}} \tag{11}$$

According to the above description of the defective wire points, BM satisfies the following condition:

$$\overrightarrow{\boldsymbol{AM}} = \lambda \overrightarrow{\boldsymbol{BM}} \tag{12}$$

From Formulae (10)-(12), vector $\overrightarrow{\boldsymbol{OM}}$ can be reduced as

$$\overrightarrow{\boldsymbol{OM}} = \frac{\lambda}{\lambda - 1}\overrightarrow{\boldsymbol{OB}} - \frac{1}{\lambda - 1}\overrightarrow{\boldsymbol{OA}} \tag{13}$$

The coordinate of point M can be got from Formula (13).

The number of times of extending depends on the wire defective degree of point cloud data. By several times of extending, if the number of points in the hollow sphere is not zero in the process of searching wire points, the new wire point is the clustering center point of points in the hollow sphere. Therefore, defective wire point is skipped by this new wire point, and the problem of defective wire data is solved.

In this paper, the number of times of extending is no more than 15, that is, when the number of points in the hollow sphere is zero in the process of searching wire, the process will continue no more than 15 times. After 15 times, if the number of points in the hollow sphere is still zero, it is considered that the process of searching one wire starting from the wire endpoint is completed. Otherwise, the new wire point is the clustering center point of points in the hollow sphere, and the searching process will continue.

To some extent, this algorithm can solve the problem of defective wire points. Some extent is related with two aspects. First, the increase of the length of defective part of one wire will lead to segmenting the wire incompletely, which will reduce the identification rate of the equipment. Second, when searching the data of the wire point cloud, the noise points around the wire will have impact on solving the problem of defective wire points. If there are too many noise points, it will change the direction of searching the wire and result in segmenting the wire incompletely. If there is no noise point around the wire, the

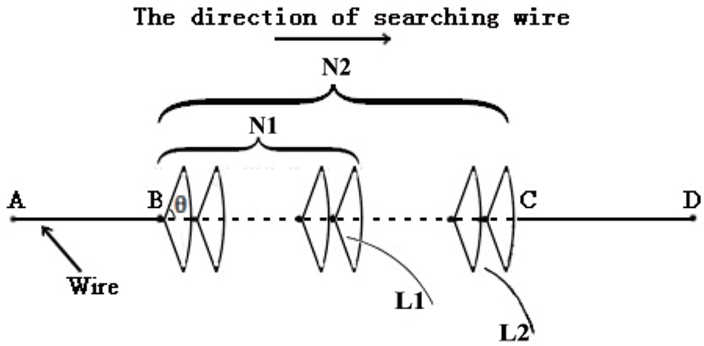


Figure 14. The process of defective wire points

segmentation of the wire will not be affected. Figure 14 explains detailedly the process of solving the problem of defective wire points.

In Figure 14, the line segments AB, CD, $L1$ and $L2$ are real substation device wire segments, and the line segment BC is the defective part of the wire AD, and θ is the angle limit of searching direction of the wire. If the number of times of extending equals $N1$, which means the extent of the defective wire points, the real wire ($L1$) is still in the search scope. In this case, the algorithm can solve the problem of defective wire points completely and segment the wire completely. If the number of times of extending, $N2$, exceeds $N1$, the real wire ($L2$) is outside the search scope. In this case, the algorithm cannot solve the problem of defective wire points completely. The parameter $N1$ is a limit of the extent of the defective wire points, which is determined by θ and the length of each extension, λ.

In this paper, by testing a large amount of actual wire point cloud data, the limit number of times of extending ($N1$) was determined to be 15, and the length of each extension (λ) is 0.0504 meters. That is, the maximum allowable length of defective part of wire is $15 * 0.0504 = 0.756$ meters. If the number of times of extending is less than 15, the algorithm can segment the wire completely. If the number of times of extending exceeds 15, the length of defect is over 0.756 meters. Such large data loss will result in loss of data integrity, and generally there is no way to compensate and segment the wire. Even if supplemented, it is often wrong and has no contribution.

4. **Experimental Results and Analysis.** The paper uses MATLAB R2014a software for simulation. The experimental point cloud data is provided by Henan Tenglong Information Engineering Co., Ltd. There are 303 test devices' point cloud data, covering more than ten categories of substation equipment, such as circuit breaker, voltage transformer, and current transformer. Mainly the experiment results are analyzed from several aspects. The first aspect is the analysis of the influence of confining searching direction on segmenting wire. The second aspect focuses on determining the parameter, θ. The last aspect is the analysis of the effect of wire segmenting algorithm.

4.1. **Effect of confining searching direction on segmenting wire.** The experimental data is the point cloud of 50 substation equipment with wire. It is found that not confining for searching direction will directly lead to the deviation of the wire direction during the searching process, and generally result in two different cases. The first case is that the algorithm can still segment the wire well, but part of the equipment body will be segmented, either, as shown in Figure 15. The second case is that the equipment's wire cannot be segmented completely, and a part of equipment body is also segmented

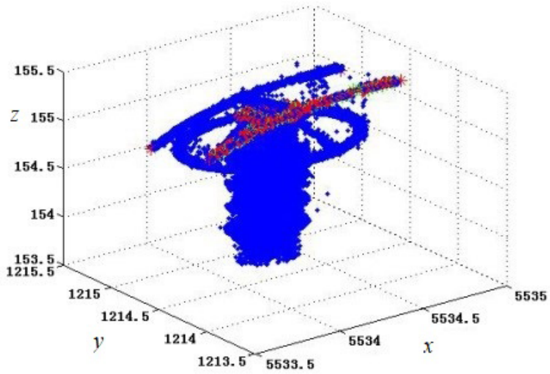


Figure 15. (color online) The first case without confining searching direction

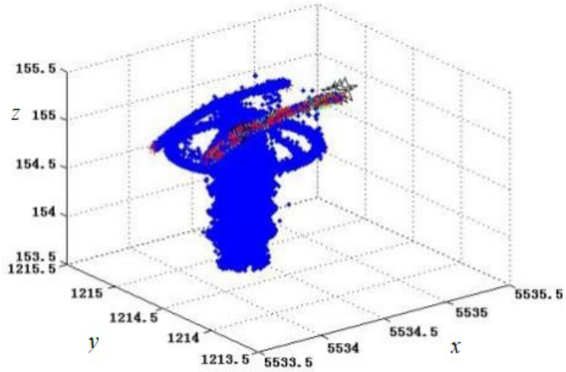


Figure 16. (color online) Confining searching direction

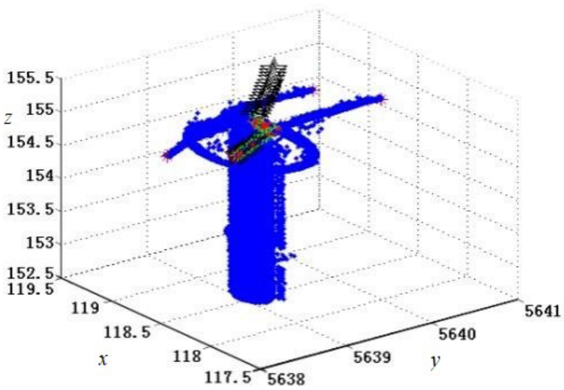


Figure 17. (color online) The second case without confining searching direction

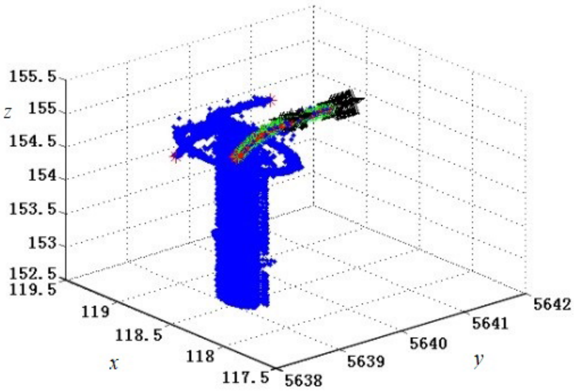


Figure 18. (color online) Confining searching direction

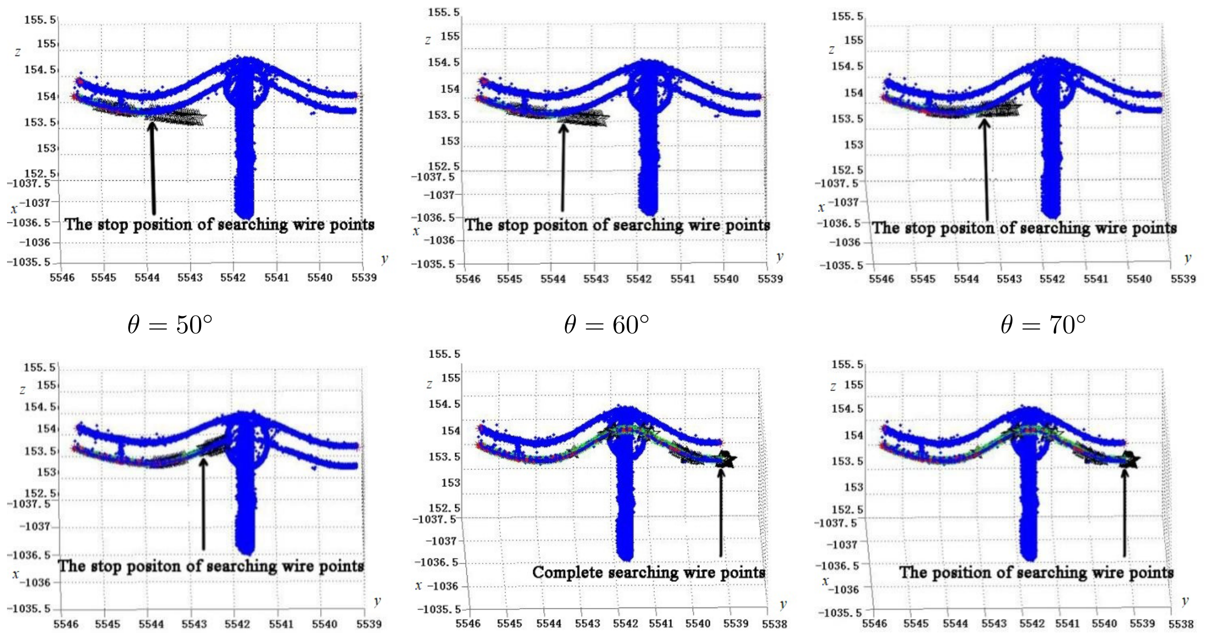
during the searching process, as shown in Figure 17. Therefore, in order to segment the equipment wire completely, the searching direction must be confined. Figure 16 and Figure 18 show the effect of confining the search direction, and the red part is the wire data produced by using the wire segmenting algorithm. It can be seen from Figure 16 and Figure 18 that the wire data which starts from an endpoint can be searched. Then two wire points can be searched after finishing the searching processes from four endpoints. The segmenting of wire can be realized by removing the wire points.

4.2. **Determining parameter θ.** The direction of searching wire is confined by the angle size of θ, which was finally determined by experiments of 50 substation devices. The experimental results are shown in Table 1.

It can be seen from Table 1 that the segmenting effect of the wire becomes better with parameter θ increasing within 85° range. If parameter θ is larger than 85°, the segmenting effect decreases with θ increasing. By the analysis of Table 1, if $\theta = 85°$, the segmenting effect is the best. Figure 19 use kV500_CP_D_7 as an example device to introduce the effect of different θ on the segmenting effect.

TABLE 1. Determining process of parameter of θ

Substation device	**Are wire segmented well?**					
	$\boldsymbol{\theta = 50°}$	$\boldsymbol{\theta = 60°}$	$\boldsymbol{\theta = 70°}$	$\boldsymbol{\theta = 80°}$	$\boldsymbol{\theta = 85°}$	$\boldsymbol{\theta = 90°}$
kV500_CP_C_1	No	No	No	Yes	Yes	Yes
kV500_CP_D_7	No	No	No	No	Yes	Yes
kV500_CT_AA_2	No	No	No	Yes	Yes	No
kV500_LA_E_1	No	No	Yes	Yes	Yes	Yes
kV500_LA_F_1	No	No	No	No	Yes	Yes
kV500_LA_G_1	No	No	No	Yes	Yes	Yes
kV500_PT_C_1	No	No	No	No	Yes	Yes
kV500_PT_E_1	No	No	No	Yes	Yes	Yes
kV500_ZUBOQI_C_7	No	No	No	No	Yes	No
kV500_CP_E_1	Yes	Yes	Yes	Yes	No	No
The number of devices segmented well	3	3	6	24	46	32



$\theta = 50°$ $\theta = 60°$ $\theta = 70°$

$\theta = 80°$ $\theta = 85°$ $\theta = 90°$

FIGURE 19. (color online) The effect of different θ on the segmenting effect

4.3. **The total effect of segmenting wire.** The following figures (Figures 20-25) use CP_C_3 as example device to show the experimental process of segmenting wire.

It can be seen from the above example that the end-points of the wire connected to the device CP_C_3 can be found accurately, and the wire connected to the device has been segmented well, which achieves the purpose of the experiment. Figures 26-28 show the comparison between the effect before and the effect after the segmenting of several devices.

The wire segmenting algorithm has been used to test 303 devices. The experimental results are shown in Table 2.

It can be seen from Table 2 that there are 275 devices with wire which have been segmented completely. Open the point cloud data of the substation devices to which the wire connected are not segmented well by Qt Reader software. It is found that the

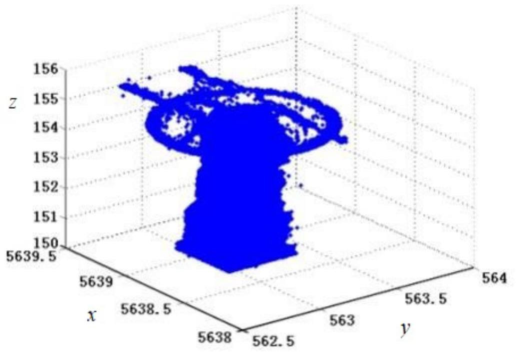


Figure 20. The device with four wire

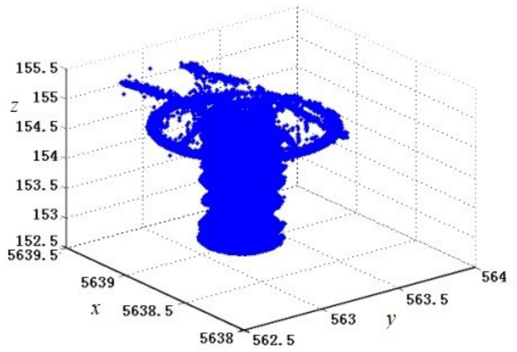


Figure 21. Preprocessing

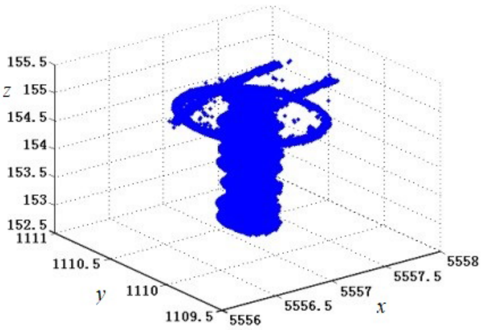


Figure 22. Changing the direction of the device

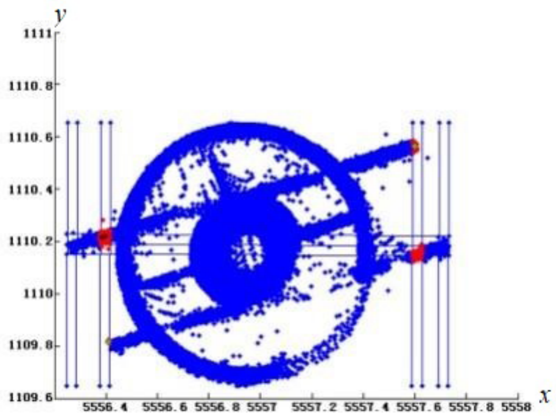


Figure 23. (color online) Finding the endpoints of the wire

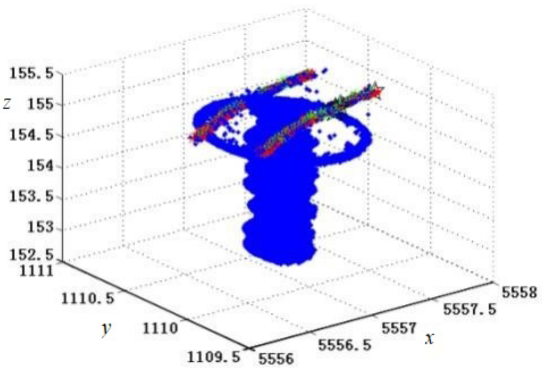


Figure 24. (color online) Using cone searching algorithm to find wire points

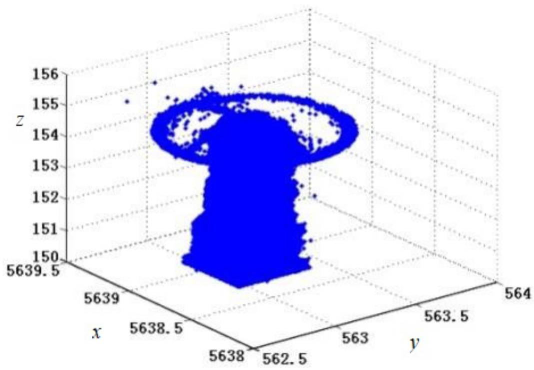


Figure 25. Removing wire points

lengths of the wire are very short for most devices, leading to that the endpoints cannot be found accurately. However, in this case, the existing wire will have a little impact on the characteristics of substation device, and will have a little impact on the identification

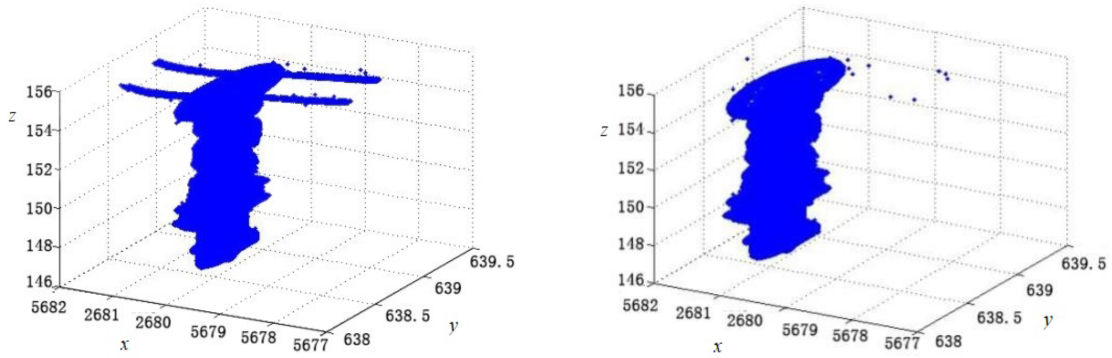


FIGURE 26. Comparison of PT_E_2 with wire with that without wire

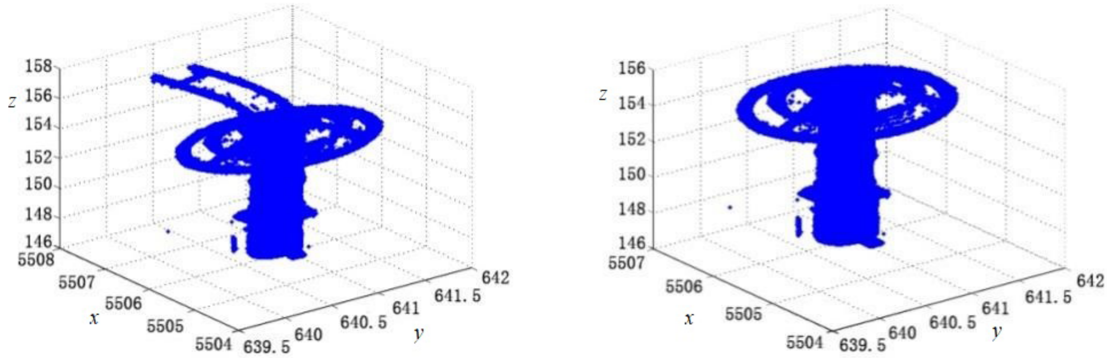


FIGURE 27. Comparison of LA_F_2 with wire with that without wire

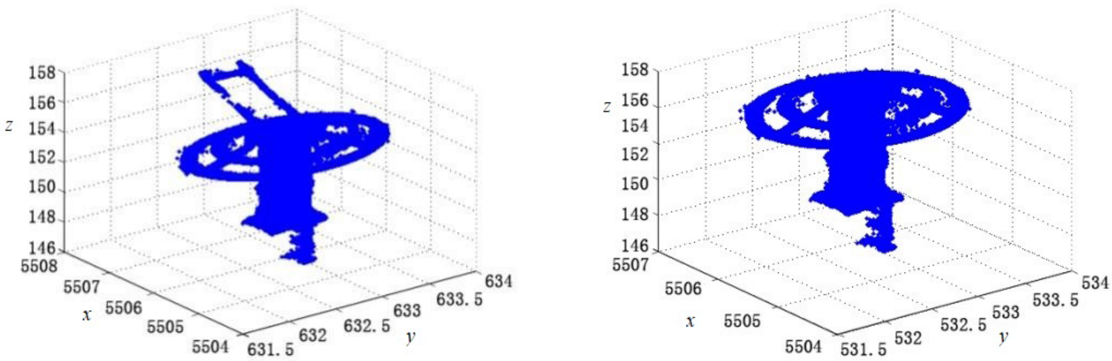


FIGURE 28. Comparison of LA_F_1 with wire with that without wire

of substation device. For other devices to which the wire connected are not segmented well, it is found that every device has a ghost and causes the wire endpoints not to be found accurately. Even if the wire endpoints can be found, the direction of searching wire points will diverge from the actual direction of wire.

5. **Conclusions.** This paper proposes a cone searching method to realize segmenting wire for substation device. First, the octree method is used to denoise point cloud data. Second, the direction of the device is changed by rotating, and two possible endpoints of the wire are found. Third, K-means clustering algorithm and the nearest neighbor

Table 2. Final segmenting results

Device number	Test device	Are wire segmented well?
1	CB_C_1	Yes
8	CP_D_5	Yes
63	DS_1D_6	No
79	DS_3DD_1	Yes
118	PT_C_2	Yes
121	PT_E_1	Yes
136	PT_F_7	No
256	DS_1AA_1	Yes
271	DS_2A_1	Yes
303	PT_A_1	No
The number of devices segmented well		275

searching method are used to find the other two possible endpoints of the wire, and judge all the four endpoints whether belonging to the endpoints of the wire. Fourth, use linear fitting based on three-dimensional point cloud to search the wire points and solve the problem of defective wire points. Then, use the cone searching method to confine the searching direction, and find out the wire points. Finally, remove all the wire points, and segmenting wire is completed. By experimenting with 303 devices, this paper's algorithm can realize segmenting wire well, and reduce the workload of manual segmenting the wire. The paper's method will play an important role in 3D identifying and reconstructing of substation equipment. However, there are some aspects where this method can be improved. In the future, the method will continue to improve the search accuracy and efficiency of endpoints, and improve the accuracy of segmentation. At the same time, the paper will study the influence of the missing degree of wires on the search-result and find the solution, so that the method can be better used in real situations.

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REFERENCES

[1] T. Yang et al., On the modeling and analysis of communication traffic in intelligent electric power substations, *IEEE Transactions on Power Delivery*, vol.32, no.3, pp.1329-1338, 2017.

[2] H. Baek, Y. Chung et al., Segmentation of group-housed pigs using concave points and edge information, *IEEE International Conference on Advanced Communication Technology*, pp.563-565, 2017.

[3] Y. Xu, S. Tuttas, L. Hoegner et al., Voxel-based segmentation of 3D point clouds from construction sites using a probabilistic connectivity model, *Pattern Recognition Letters*, vol.102, pp.67-74, 2018.

[4] S. Jin, Y. Su, S. Gao et al., Deep learning: Individual maize segmentation from terrestrial LiDAR data using faster R-CNN and regional growth algorithms, *Frontiers in Plant Science*, 2018.

[5] P. Polewski, W. Yao, M. Heurich et al., Learning a constrained conditional random field for enhanced segmentation of fallen trees in ALS point clouds, *ISPRS Journal of Photogrammetry & Remote Sensing*, pp.33-44, 2017.

[6] D. Chen, L. Zhang, P. T. Mathiopoulos et al., A methodology for automated segmentation and reconstruction of urban 3-D buildings from ALS point clouds, *IEEE Journal of Selected Topics in Applied Earth Observations & Remote Sensing*, vol.7, no.10, pp.4199-4217, 2014.

[7] Y. Zhou, D. Wang, X. Xie et al., A fast and accurate segmentation method for ordered LiDAR point cloud of large-scale scenes, *IEEE Geoscience & Remote Sensing Letters*, vol.11, no.11, pp.1981-1985, 2014.

[8] O. Jaehong and L. Changno, 3D power line extraction from multiple aerial images, *Sensors*, vol.17, no.10, pp.2244-2258, 2017.

[9] J. Huang, H. Gao and Z. Dai, Semantic segmentation method of power line for mobile terminal based on encoding and decoding structure, *Journal of Computer Applications*, vol.41, no.10, pp.2952-2958, 2021.

[10] S. Sharifzadeh, I. Biro, N. Lohse et al., Abnormality detection strategies for surface inspection using robot mounted laser scanners, *Mechatronics*, vol.51, pp.59-74, 2018.

[11] M. Ferreira, A. P. Moreira and P. Neto, A low-cost laser scanning solution for flexible robotic cells: Spray coating, *International Journal of Advanced Manufacturing Technology*, vol.58, nos.9-12, pp.1031-1041, 2012.

[12] W. Guo, Y. Ji, Y. Luo and Y. Zhou, Substation equipment 3D identification based on KNN classification of subspace feature vector, *Journal of Intelligent Systems*, 2017.

[13] Q. Xie and X. Xie, Point cloud data reduction methods of octree-based coding and neighborhood search, *Electronic & Mechanical Engineering and Information Technology*, vol.7, pp.3800-3803, 2011.

[14] X. Zeng, Z. Li, W. Gao et al., A novel virtual sensing with artificial neural network and K-means clustering for IGBT current measuring, *IEEE Transactions on Industrial Electronics*, no.99, pp.184-194, 2018.

[15] C. M. Shakarji and V. Srinivasan, Optimality conditions for constrained least-squares fitting of circles, cylinders, and spheres to establish datums, *ASME 2017 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference*, 2017.

[16] A. Araújo, Polynomial regression with reduced over-fitting – The PALS technique, *Measurement*, 2018.

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