

An automatic extraction algorithm of high voltage transmission lines from airborne LIDAR point cloud data

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Abstract: To improve the effectiveness and generality of existing methods of high voltage (HV) transmission lines extraction, this paper proposes a novel automatic extraction method of HV transmission lines using airborne LIDAR point cloud data by incorporating the geography of transmission corridors and the distribution characteristics of airborne LIDAR point cloud data. The proposed method results in the separation of ground objects by using a differentiation height threshold segmentation algorithm based on subspace features, which divide long-distance space into several small-distance space sets to improve the generality of the algorithm. A height density segmentation algorithm is used to locate transmission towers and extract point cloud data of HV transmission lines to improve the efficiency of the algorithm. Feasibility test cases show that the proposed method can automatically extract HV transmission lines from airborne LIDAR point cloud data in flat terrains, canyon terrains, and steep slope terrains in an efficient manner, with high accuracy and generality.

Key words: Transmission line, airborne LIDAR, point cloud data, extraction algorithm

1. Introduction

The increasing number of high voltage (HV), large capacity transmission lines, as well as the increasingly complex geographical environment along the transmission corridors, have introduced a series of difficulties into the maintenance of HV transmission lines [1]. Light detection and ranging (LIDAR), an emerging remote sensing technique that uses laser pulses to produce accurate measurements, densely integrates advanced modules such as GPS, INS, and laser scanning rangefinders and can efficiently acquire 3D coordinates of objects with high precision [2,3]. Due to the high penetration of laser pulses, LIDAR can swiftly detect surface information beneath vegetation cover. For this reason, it has a unique superiority in acquiring 3D information of transmission corridors in complex terrains, or even hazard zones [4–6]. Airborne LIDAR has received widespread attention and application in the field of HV transmission line inspection, such as monitoring and safety warning [7,8], management and planning [9,10], and 3D power line extraction and reconstruction [11,12].

The key issues of airborne LIDAR HV transmission line inspection technology include point cloud data acquisition, point cloud data segmentation and extraction, 3D fitting and reconstruction, and measurement and evaluation. Because massive point cloud data are generated for the HV transmission line inspection technique based on airborne LIDAR, a fast and efficient segmentation and extraction algorithm for point cloud data of

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ground objects, transmission towers, transmission lines, and accessories along the transmission corridor will directly affect the time-effectiveness of this technique and its value for engineering applications [12,13]. As indicated by recent studies, the automatic extraction of transmission lines has gained some attention, but related research is still in its infancy. The results of representative studies are introduced as follows: reference [14] proposed a data segmentation algorithm based on height threshold segmentation to eliminate ground object points; however, this algorithm is applicable only to flat terrains with small interference, while zones with large fluctuation and many interferences have poor effects. Reference [15] adopted a filtering method based on the angles separating points of vegetation cover and those of transmission lines. It separates different transmission lines using 2D Hough transforms; a hyperbolic cosine function is used to fit single transmission lines, with poor results for transmission line extraction in terrains with transmission lines mingled with trees. Reference [16] proposed an automated power line detection method for forest environments based on statistical analysis and 2D image-based processing technology, but it has some problems, as it is time-consuming and performs incomplete extraction. Reference [17] proposed a filtering algorithm based on the pattern classification of local height histograms and chose separate threshold values to classify point cloud distributions into 3 patterns: transmission lines, transmission towers, and surface points. However, in some cases, it might falsely classify the points representing the cross arms of transmission towers as transmission lines, with a low level of automation. Reference [18] presented a new classification method of power lines in urban areas that uses 4 steps: power line candidate point filtering, local neighborhood selection, spatial structural extraction, and SVM classification. The precision is more than 98%, but the algorithm is slightly complex for simple terrains.

As noted above, several methods have been utilized for transmission line extractions from airborne LIDAR point cloud data, but these existing methods are mostly targeted at particular terrain types, with limited algorithmic reliability and generality. Moreover, in the field, transmission lines obtain hugely diversified point cloud distributions when going through plain areas, hilly areas, canyon areas, mountain areas, etc. The methods for transmission line extraction in flat areas have little to no precision in undulating areas such as forests and mountains. Similarly, the methods suitable for undulating areas are inefficient when used in flat areas. The precise and efficient extraction of point clouds of transmission lines is the key to fitting and rebuilding models of transmission lines, as well as providing basic data for transmission line inspection and its subsequent application, analysis, and evaluation, which directly affects the application of these measurements and the estimation of 3D real scenes.

Thus, there is an urgent need for efficient extraction methods for transmission lines in multiple terrains from point cloud data. To address this goal, this study proposes a height threshold segmentation algorithm based on subspace features, as well as a height density segmentation algorithm to segment point cloud data of ground objects and transmission towers. These algorithms take into account the geography of overhead transmission corridors and the data structures of airborne LIDAR point clouds of transmission lines. This allows us to realize the efficient and precise extraction of transmission lines for multiple terrains from an airborne LIDAR point cloud.

2. Terrain of HV transmission line corridors and the characteristics of airborne LIDAR point cloud data

2.1. Terrain types of HV transmission line corridor

With the development of power transmission technology, ultrahigh voltage and extrahigh voltage transmission lines are extending across increasingly long distances, usually through multiple terrains such as plains, canyons,

and steep slopes, as shown in Figure 1.

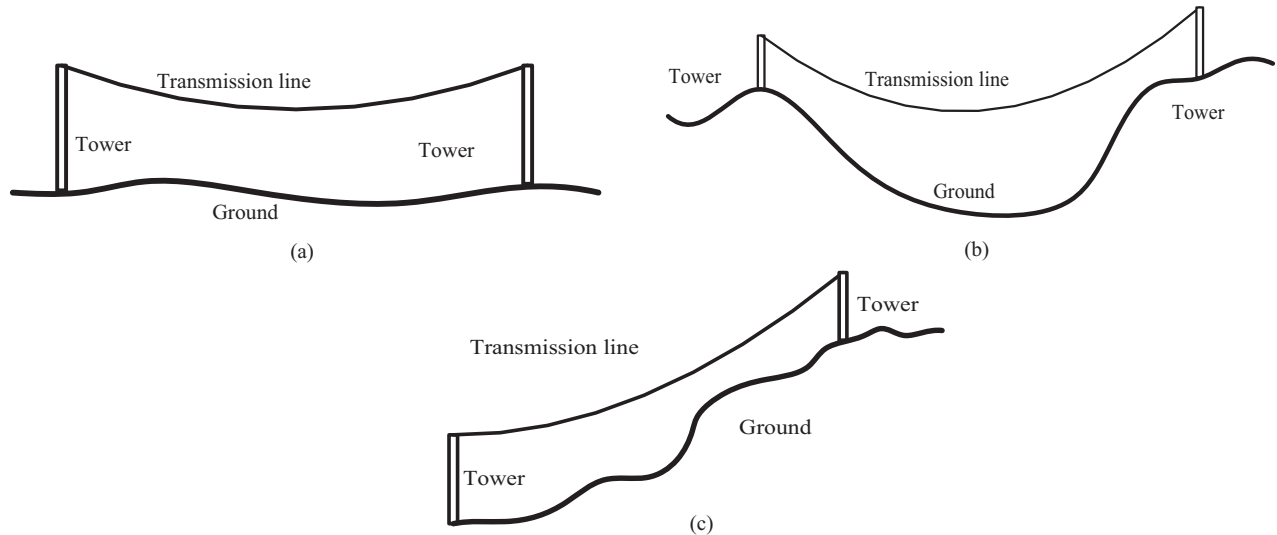


Figure 1. Typical terrain of transmission line corridors: a) plain area, b) canyon area, c) steep slope area.

As Figure 1a shows, plain areas have small changes in height, with a significant difference between the height of the transmission lines and that of the ground surface. On the other hand, canyons and steep slopes have abrupt changes in height, resulting in recurring small differences between the heights of transmission lines and the ground surface, as shown in Figures 1b and 1c.

The distribution profile of transmission lines in canyon zones is approximately equivalent to that of 2 steep slopes, as shown in Figure 2.

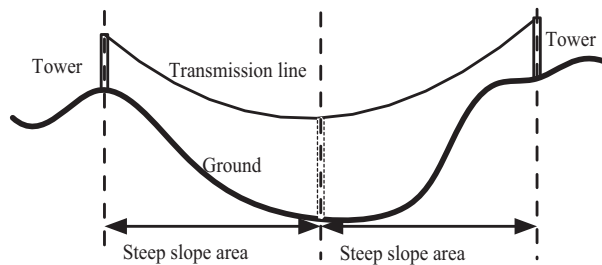


Figure 2. The canyon area equivalent of 2 steep slope areas.

In summary, terrains in transmission corridors can be considered as combinations of 2 basic topographies: comparatively flat terrain with slow changes in height (flat segments), and highly fluctuating terrain with complicated topography (steep slope segments).

2.2. Features analysis of airborne LIDAR point cloud of HV transmission lines

In China, the scanning bandwidth of 110 kV to 500 kV transmission lines is around 50 m on both sides of the conductor, which is 75 m for ± 660 kV and 750 kV transmission lines by airborne LIDAR, and the acquisition density of point cloud is generally 36–50 points/m². Figure 3 shows the airborne LIDAR point cloud data of actual HV transmission lines.

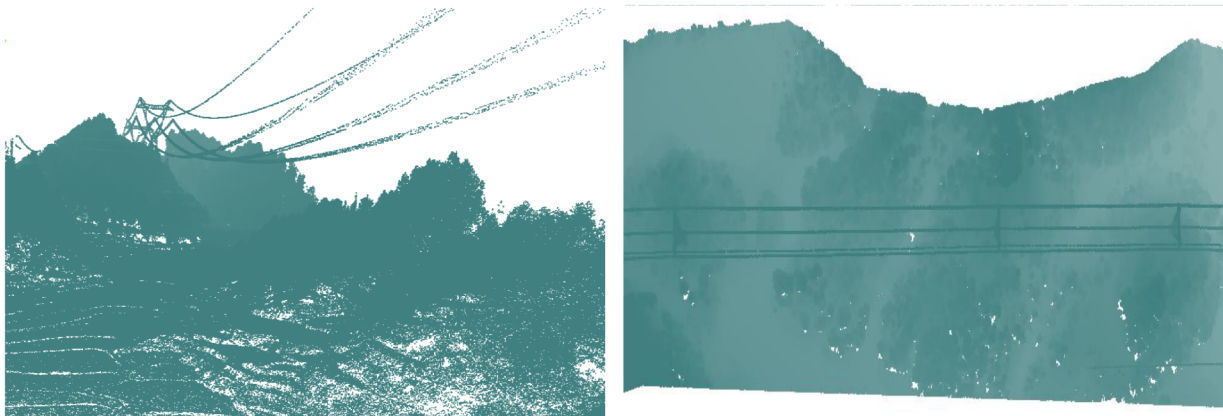


Figure 3. Airborne LIDAR point cloud data of HV transmission lines.

As shown in Figure 3, airborne LIDAR point cloud data obtained from HV transmission lines include point clouds of transmission lines, transmission towers, and ground objects. The automatic recognition and separation of points of transmission towers and ground objects is a necessary step to realize the automatic extraction of point cloud data of transmission lines. In addition, the knowledge of the distribution and structure of airborne LIDAR point cloud data of transmission lines is foundational for the precise segmentation and efficient extraction of point cloud data of ground objects, transmission towers, and transmission lines. Figure 4 shows a schematic map of airborne LIDAR point cloud data of transmission lines in 2 basic topographies.

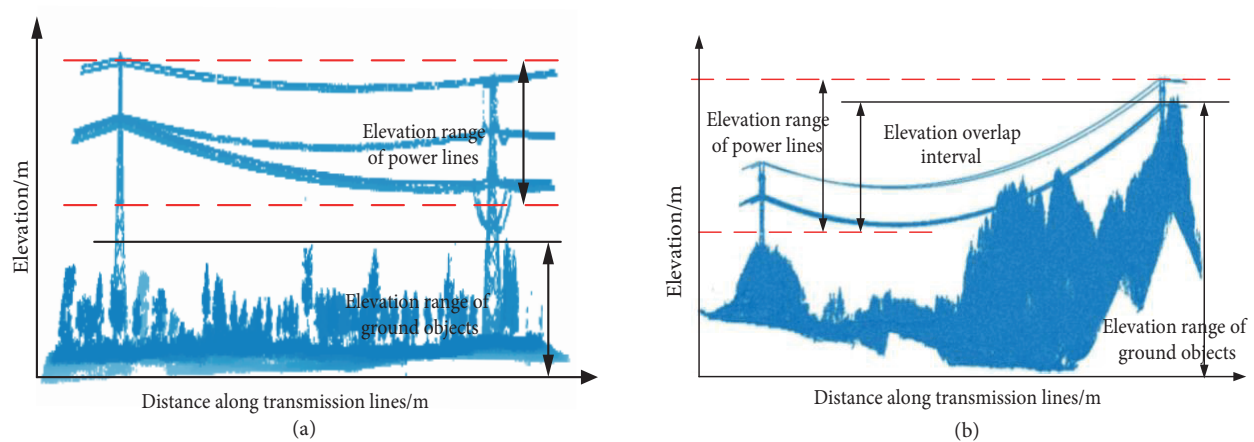


Figure 4. Elevation distribution diagram of point cloud: a) flat area, (b) steep slope area.

As seen in Figure 4a, in flat zones with small height variations, such as plains, transmission towers are of similar heights; the height distribution space of point cloud data of transmission lines has no superposition with that of ground objects. However, as seen in Figure 4b, in zones with large fluctuations in height, neighboring towers are often of different heights, with some height differences that are even greater than the height of a tower itself. Therefore, the height distribution of point cloud data of transmission lines and that of ground objects will overlap to some extent, and the superposition of these height distributions will occur.

In some zones, the distributions of points of ground objects, towers, and transmission lines have the following features, from low to high: points of ground objects are distributed continuously throughout the

whole region, with low height; points of towers are concentrated, with a broad range of height, while their horizontal projection is basically distributed within a small rectangle with high density. Points of transmission lines are distributed linearly in 3 dimensions; due to security considerations, they generally have the largest height difference with the ground, and they are loosely distributed.

As shown in Figure 5, within small distances along a transmission line, clear height distributions of ground objects, towers, and transmission lines are observed, featured by flat terrains that can be easily generalized. In a local range, heights of transmission lines and towers are significantly greater than that of the ground, which makes it possible to convert the recognition of point clouds of steep slope terrains into a combination of small flat terrains.

3. Extraction algorithm proposed

The automatic recognition and extraction of point cloud data of transmission lines involves 2 basic steps: the recognition and segmentation of ground objects and towers.

3.1. Recognition and segmentation algorithm of point cloud data of ground objects

The feasibility and effectiveness of ground objects separation and transmission line extraction of transmission line corridors in flat terrains from airborne LIDAR point clouds based on elevation have been verified. The main challenge for the engineering application of this method is the universality in multiple terrains [14,17]. As mentioned in Section 2, ground object points cannot be separated from nonground object points using height distribution features in highly fluctuating terrains. However, in a local range, heights of transmission lines and towers are significantly greater than that of the ground, which makes it possible to convert the recognition of point clouds of steep slope terrains into a combination of small flat terrains. On such a basis, this study proposes a height threshold segmentation algorithm based on subspace features to eliminate the point cloud data of ground objects. The procedures are as follows:

First, the boundary values of the original point cloud data are calculated to determine the distribution space of the initial point cloud M_0 :

$$\left\{ \begin{array}{l} x_{\min} = \min(x) \\ x_{\max} = \max(x) \\ y_{\min} = \min(y) \\ y_{\max} = \max(y) \\ z_{\min} = \min(z) \\ z_{\max} = \max(z) \end{array} \right. , \quad (1)$$

where (x, y, z) indicates the 3D coordinates of an arbitrary point.

Second, a segmentation scale d_x , which is appropriate to a specific situation, is selected to divide the whole point cloud space into n subspaces along the X coordinate, as is shown in Eq. (2) and Figure 6:

$$n = \lfloor (x_{\max} - x_{\min}) / d_x \rfloor + 1. \quad (2)$$

Then Eq. (3) is used to calculate the height difference δ_i of point clouds in each subspace $M_i (i=1, 2, \dots, n)$, using δ_i as the feature value of subspace M_i .

$$\delta_i = z_{\max} - z_{\min} \quad (3)$$

Finally, a threshold value δ_z is set, based on which the feature value δ_i is used to classify subspaces.

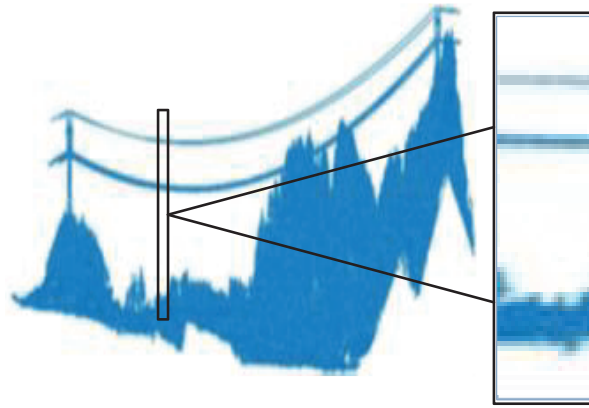


Figure 5. The distribution of point clouds on the small-distance scale of steep slope area.

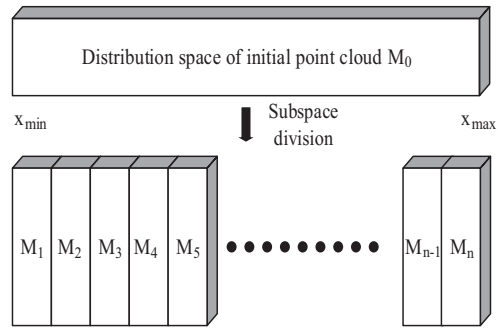


Figure 6. Subspace division based on the X axis.

If $\delta_i > \delta_z$, then the subspace is classified into class A.

If $\delta_i \leq \delta_z$, then the subspace is classified into class B.

Due to different scanner models and scanning accuracy, the quality of the collected point cloud varies. Therefore, the δ_z setting should be based on the actual point cloud quality and the size of the subspace. When the size of the taken subspace is large and the collected point cloud density is high, a larger threshold value should be set; on the contrary, the threshold value may be appropriately reduced.

Point clouds in subspace class B can be treated as those of pure ground objects; point clouds in subspace class A contain those of both ground and nonground objects.

Subspaces of class A should be further segmented using the height threshold segmentation algorithm.

Height values z_i of each point in the original cloud must be calculated. Eq. (4) is used to calculate the average height of all points. In this formula, n represents the number of point clouds:

$$\bar{z} = \frac{\sum_{i=1}^n z_i}{n}. \tag{4}$$

The whole point cloud is divided into top and bottom parts according to \bar{z} . The average heights of the points of both parts, \bar{z}_1 and \bar{z}_2 , are calculated. The average value of \bar{z}_1 and \bar{z}_2 is used as a new \bar{z} . This step is repeated until \bar{z} is stabilized within a certain range. The whole point cloud is then divided into 2 parts based on \bar{z} . Specifically, points with height values less than \bar{z} are ground objects, while points with height values greater than \bar{z} are nonground objects (namely, towers and transmission lines, as well as some trees and slope tops), as shown in Figure 7.

The process of eliminating ground object points using the height threshold segmentation algorithm based on subspace features is shown in the flow chart in Figure 8.

3.2. Algorithm of tower identification and segmentation

Following the identification and segmentation of the ground objects mentioned above, there are still some nonground object points present that contain transmission lines and towers, as well as minor trees and slope tops. To extract point clouds of transmission lines, the point clouds of towers, trees, and slope tops should be further eliminated. The analysis of point clouds shows that the density of points representing towers, trees,

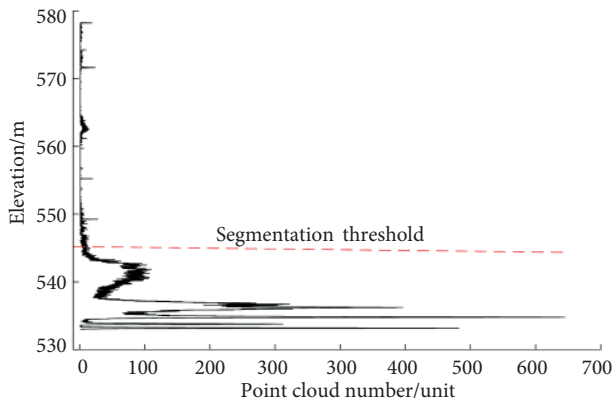


Figure 7. Height distribution histogram and threshold selection.

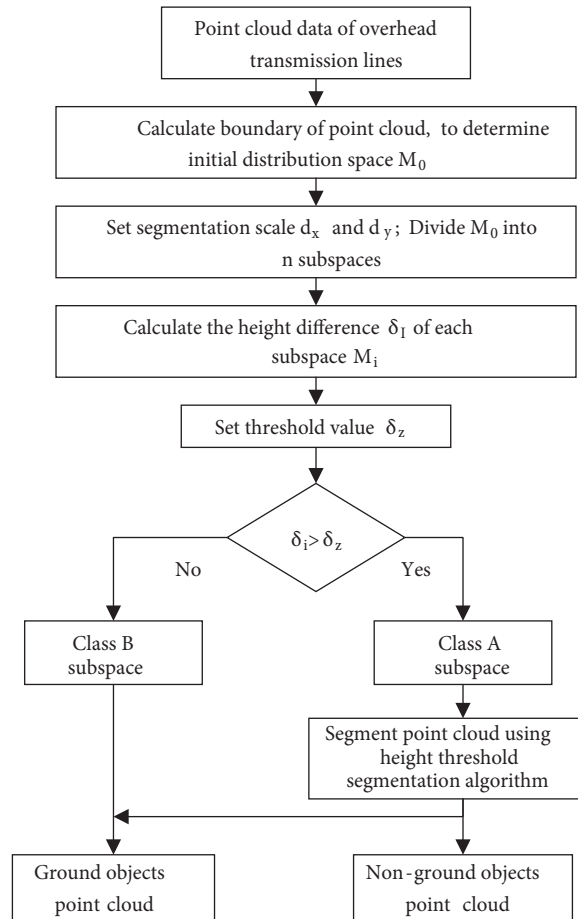


Figure 8. Flow chart of the height threshold segmentation algorithm based on subspace features.

and slope tops is greater than that of transmission lines; therefore, density differences can be used to eliminate these points. For convenience, points representing towers, trees, and slope tops are collectively referred to as “tower points” in the following section. This study proposes a height density segmentation algorithm to realize the recognition and segmentation of towers and remaining objects. The procedure is as follows:

First, the boundaries between the point clouds of towers and transmission lines are located to determine the initial space of the point cloud M_0 .

Second, the segmentation scales d_x and d_y are used to divide the initial space M_0 along the X and Y coordinates into $m \times n$ subspaces $M_{i,j} (i = 1, 2, \dots, m; j = 1, 2, \dots, n)$, as is shown in Eq. (5) and Figure 9:

$$\begin{cases} m = \lfloor (x_{\max} - x_{\min})/d_x \rfloor + 1 \\ n = \lfloor (y_{\max} - y_{\min})/d_y \rfloor + 1 \end{cases} \quad (5)$$

Then the number of point clouds $C_{i,j}$ in each subspace $M_{i,j}$ is counted and used as the feature value of this subspace.

The threshold value C_0 is then set, and all subspaces are classified into 2 classes according to C_0 . Specifically, points of a subspace with height values greater than the threshold value C_0 are classified as tower

points, while those with height values less than the threshold value C_0 are classified as transmission line points. As with δ_z , the C_0 setting should also be based on the actual point cloud quality and the size of the subspace.

Finally, subspaces belonging to points of towers and transmission lines are extracted. Thus, the segmentation of towers and transmission lines is completed, so that the extraction of point cloud data of transmission lines is realized.

A flow chart depicting the recognition and segmentation process of towers and remaining objects based on the height density segmentation algorithm is shown in Figure 10.

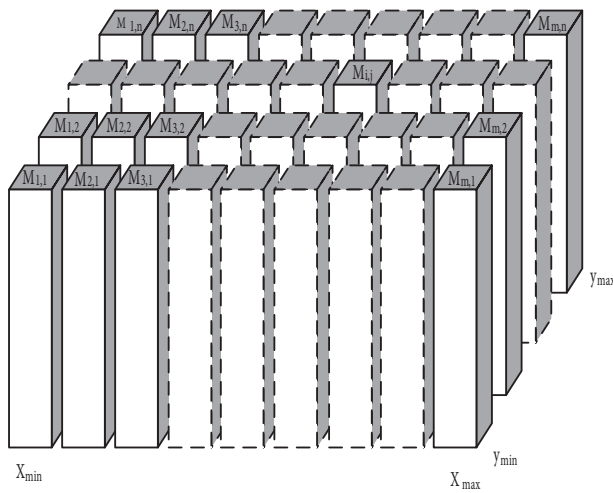


Figure 9. Subspace division based on X and Y axes.

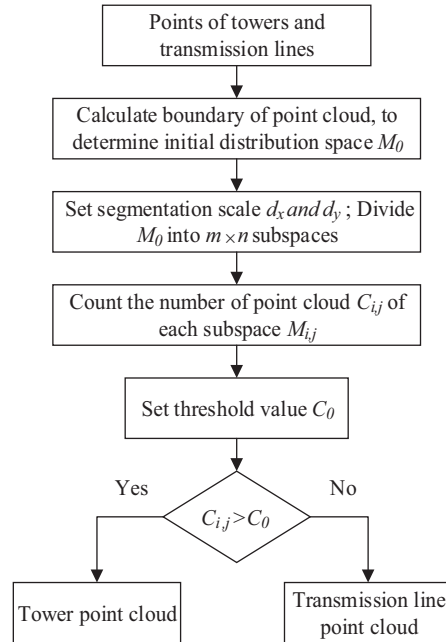


Figure 10. Flow of height density segmentation.

4. Case study

To verify the feasibility of the algorithm of automatic extraction of transmission lines, data are used from some sections of towers for outgoing transmission lines of the 500 kV Fenghuangshan substation, as measured by airborne LIDAR. The data are single-span point clouds for both flat and steep slope terrains, with spans of 210.8 m and 608.5 m, respectively. MATLAB 2016a, which has good algorithmic calculating performance and visual demonstration, is used to carry out the algorithmic testing and the resulting demonstration to support the feasibility test.

In China, the size of the grid is 2.5 m × 2.5 m when laser point cloud data are used to generate DEM [19]. Therefore, in order to meet the rules and have high accuracy as well, the segmentation of the ground objects is set to $\mathbf{d_x} = \mathbf{5\ m}$, and the segmentation of the recognizing towers is set to $\mathbf{d_x} \times \mathbf{d_y} = \mathbf{05\ m} \times \mathbf{05\ m}$. The test results are shown in Figures 11a, 11b, 12a, and 12b.

First, a height threshold segmentation algorithm based on subspace features is used to carry out the identification and segmentation of ground objects. Point cloud data of towers and transmission lines for flat terrain and steep slope terrain, after segmenting the ground objects, are shown in Figure 11a and Figure 12a, respectively.

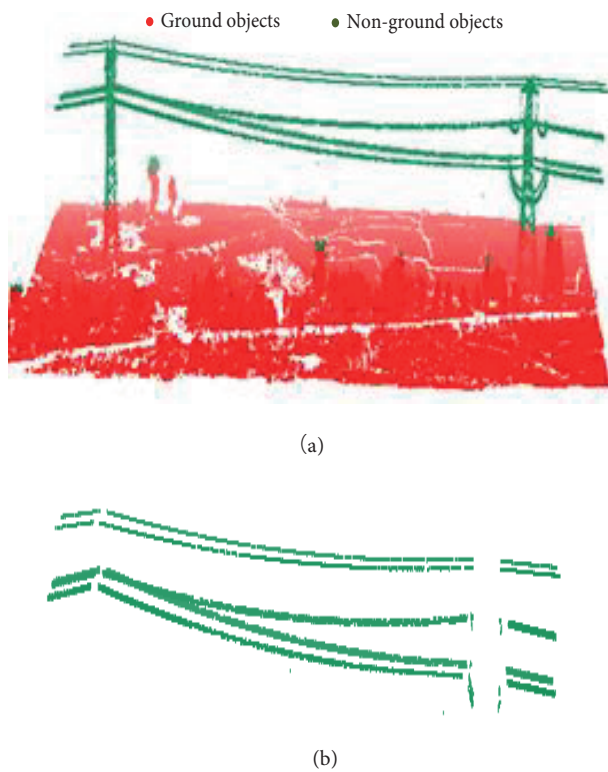


Figure 11. Testing results of flat terrain: a) ground objects point cloud data filter result; b) transmission line point cloud data extraction result.

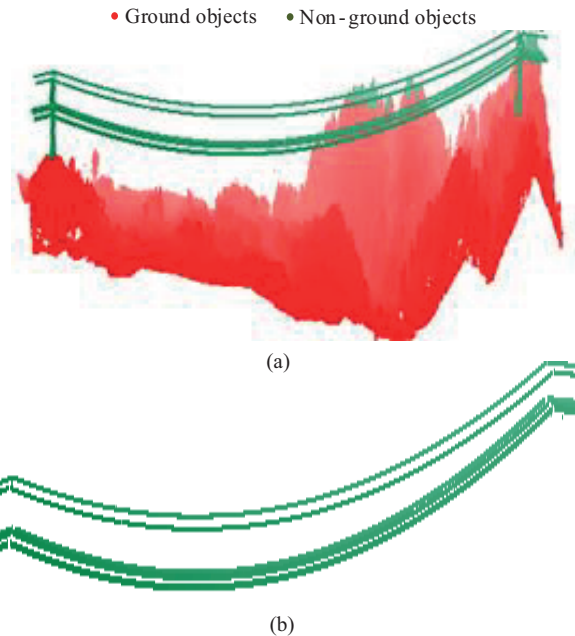


Figure 12. Testing results of steep slope terrain: a) ground objects point cloud data filter result; b) transmission line point cloud data extraction result.

As can be seen, using the proposed algorithm, ground object points can be effectively eliminated in both flat and steep slope terrains (illustrated in red in the figures). While a small number of points of trees, slope tops, and towers remain, the points of transmission lines are completely preserved.

In the next step, the segmentation of tower points (including a small number of trees and slope tops) and the recognition and extraction of transmission lines are carried out according to a height density segmentation algorithm, as shown in Figure 11b and Figure 12b.

As can be observed from Figure 11 and Figure 12, except for some mistakenly eliminated point clouds of transmission lines due to interference from neighboring towers, the point clouds of most zones are perfectly recognized and extracted.

In order to verify the validity of the proposed algorithm, we compared the difference between the proposed algorithm and the traditional method, the height threshold segmentation method mentioned in reference [14]. The results of the traditional method are shown in Figures 13a, 13b, 14a, and 14b.

By comparing the experimental results of the proposed algorithm with those of the traditional algorithm, we can see that in the flat areas where the terrain changes little, the proposed algorithm is basically the same as the traditional algorithm in nonterrain points and the power line extraction results. However, the traditional algorithm has poor extraction results and part of the power line points are removed, resulting in only a small fraction of the power line point cloud extraction success. The proposed algorithm effectively solves this problem.

To further verify the robustness of the proposed algorithm, 6 groups of point cloud data of single-span transmission lines on flat terrain (with spans of 210.8 m, 215.5 m, 354.2 m, 330.2 m, 269.8 m, and 450.9 m,

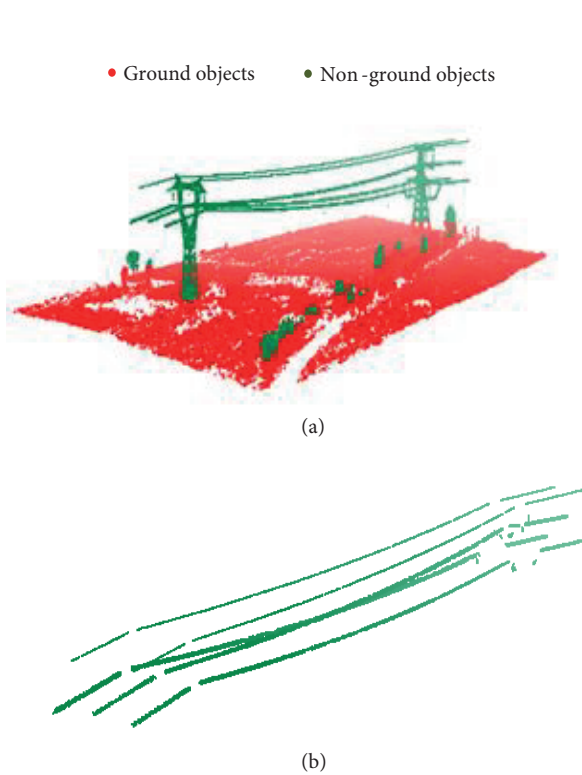


Figure 13. Testing results of flat terrain: a) ground objects point cloud data filter result; b) transmission line point cloud data extraction result.

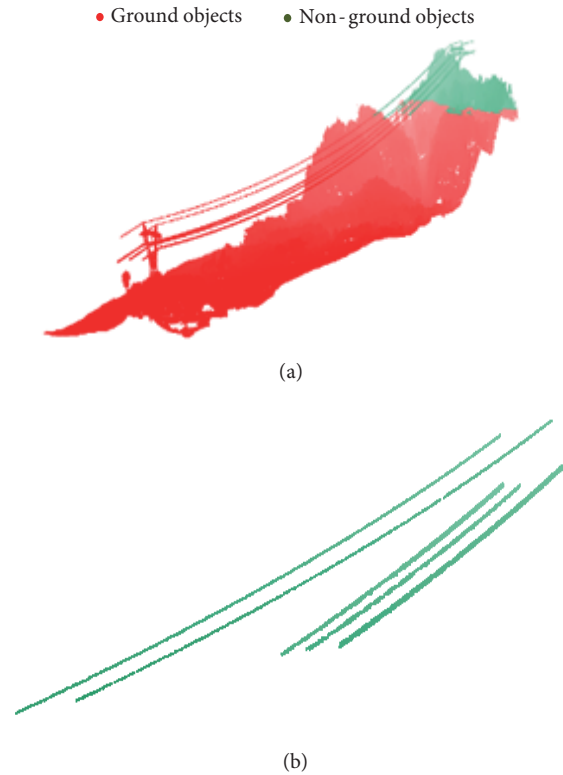


Figure 14. Testing results of steep slope terrain: a) ground objects point cloud data filter result; b) transmission line point cloud data extraction result.


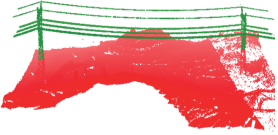
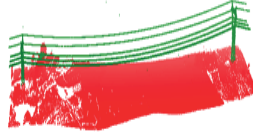
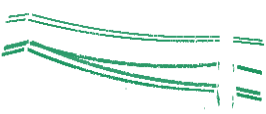
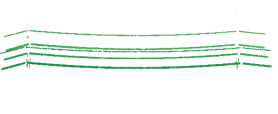
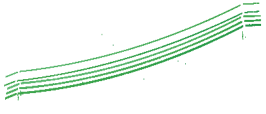
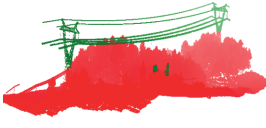

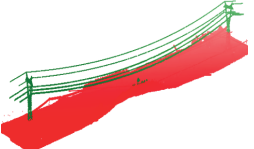
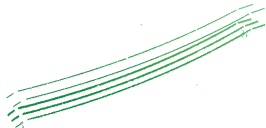
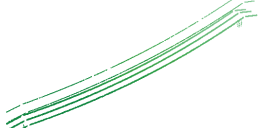
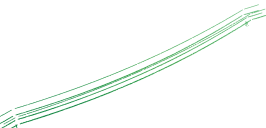
denoted as No. 1, No. 2, No. 3, No. 4, No. 5, and No. 6, respectively) are used for this test. The number of point clouds extracted for each data sample is counted. A manual recheck of the extracted point clouds of transmission lines is carried out. Specifically, points other than those of transmission lines are manually deleted, and the number of the remaining effective points of transmission lines is counted. The ratio of the number of effective points to the number of extracted points is treated as the accuracy ratio for the extraction of point clouds of transmission lines. The results are shown in Tables 1 and 2.

Table 1. Comparison of extraction results in flat areas.

Order number	No. 1	No. 2	No. 3	No. 4	No. 5	No. 6
Number of original points	511,395	749,187	817,377	831,395	749,187	107,377
Extracted point number by proposed method	9411	12,534	14,306	13,911	12,534	17,306
Extracted point number by hand	9148	11,986	14,064	13,521	11,986	17,012
Correctness	97.2%	95.6%	98.3%	97.2%	95.6%	98.3%

As Table 1 shows, the number of automatically extracted point clouds of transmission lines is slightly larger than that of manually extracted point clouds. The reason for this is that a small number of noise points with similar features exist in the neighboring area of the point clouds of transmission lines, and these points are not effectively eliminated by the proposed method. Even in such a situation, the proposed method still has an accuracy rate of above 95%, which satisfies the engineering application requirements. Of course, theoretically,

Table 2. Extraction results of transmission line point cloud data.

Order number	No. 1	No. 2	No. 3
Filter result			
Extraction result			
Order number	No. 4	No. 5	No. 6
Filter result			
Extraction result			

the existence of noise points will interfere with the fitting precision of transmission lines, especially suspension and maximum sag points. A correction scheme for point clouds of transmission lines should be explored to further improve extraction accuracy.

In this study, the segmentation threshold of each subspace is obtained by dividing a whole point cloud space into several subspaces, based on which ground object points are eliminated. Theoretically, the length of each subspace d_x will affect the extraction precision and the efficiency of transmission lines. To quantify the influence of the length of subspace d_x on the extraction precision and efficiency, an experiment on the extraction of transmission lines is carried out by setting the length of subspace d_x using No. 3 data. The experiment results are shown in Table 3.

Table 3. Extraction results with different subspace lengths.

Subspace length (m)	Correctness	Run time (s)
1	85.9%	17.6
3	92.2%	14.7
5	98.3%	12.9
10	97.8%	10.5
20	97.9%	9.3
50	97.5%	8.7
100	97.1%	8.4

As Table 3 shows, with increasing length of subspace \mathbf{d}_x , the extraction accuracy rises before it falls slowly, and the execution time of the algorithm drops with increasing of \mathbf{d}_x . It can be concluded, based on the principle of the extraction algorithm, that when \mathbf{d}_x is small, because the number of point clouds within a subspace is small, the segmentation threshold is affected by noise points, resulting in the low precision of extraction. Multiple rounds of threshold calculation lead to longer execution times. In a certain range, with the increasing length of a subspace \mathbf{d}_x , interference from noise points decreases and the precision of extraction increases. With the reduction of the number of subspaces, the execution time is lowered. With the further increase in the length of a subspace \mathbf{d}_x , the time consumption is further reduced; however, some abnormal data such as tree tops cannot be effectively recognized locally, leading to a decrease in the recognition precision. The use of a reasonable range of values of the subspace length \mathbf{d}_x is thus very crucial.

In summary, the proposed extraction algorithm can effectively realize the accurate extraction of transmission lines for both flat and steep slope terrains, with an extraction precision of no less than 95%, thus indicating its engineering value. A reasonable selection of the segmentation length of a subspace is beneficial to achieve a balance between the extraction precision and the execution efficiency of transmission lines.

5. Conclusion

The automatic extraction algorithm of transmission lines proposed in this paper can effectively realize the accurate extraction of point cloud data of transmission lines for both flat and steep slope terrains with high generality and reliability, which represents a valuable solution to the extraction of point cloud data of transmission lines in multiple terrains. The length of a subspace affects the precision and efficiency of extraction; therefore, further studies are needed to develop methods of self-adaptive value selection for selecting subspace lengths in multiple terrains, with a view to balance extraction precision and efficiency.

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