RESEARCH ON POWER TRANSMISSION CHANNEL CHANGE DETECTION BASED ON MULTI-TEMPORAL POINT CLOUD DATA

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KEY WORDS: ICP Algorithm, Change Detection,Point Cloud Registration, Multi-temporal Point Cloud.

ABSTRACT:

Airborne LiDAR can directly obtain 3D information of ground objects. By comparing the multi-temporal LiDAR data, ground objects change information of power transmission channel can be detected, providing data support for transmission line operation and maintenance. In this paper, an improved ICP algorithm based on multi-temporal LiDAR point cloud data power transmission channel ground object change detection method is proposed. Firstly, based on the classification of point cloud data, a two-level matching method of multi-temporal point cloud data considering the characteristics of power transmission channel was proposed to achieve accurate registration of point cloud data. Then, change detection and analysis of different types of ground feature point cloud data were carried out through elevation difference. Finally, cluster analysis was carried out on the changed ground feature points to generate multi-temporal relative ratio analysis report. Experimental results show that the proposed method can effectively detect power transmission channel changes.

1. INTRODUCTION

Airborne three-dimensional laser scanning can directly obtain the geometric parameter morphology of transmission lines and ancillary facilities[1], providing a new means for power inspection[2]. The dynamic change of channel ground features is an important factor affecting the security and stability of power grid. The change of channel ground features can be analyzed by comparing the multi-temporal point cloud data of transmission channel, so as to improve the lean management level of power transmission channel.

Peng Daifeng et al. proposed a change detection method for urban buildings based on LiDAR data and image data. Firstly, the DSM is generated by LiDAR point cloud data in different periods, and then the DSM variation region is obtained by difference, filtering and morphological operation for the DSM in different periods. According to the collinear equation, it is backprojected into the aerial image, and then the spectral and texture information of the aerial image is used to eliminate the interference in the pseudo-variation areas such as trees. Finally, the elevation change value and the area change value of the building are calculated. Zhang Liang[4] proposed multi-level local ICP-matched terrain 3D change detection and multi-temporal LiDAR point cloud building 3D change detection. By analyzing the spatial differences of point clouds in different phases, SVM algorithm was introduced to realize automatic classification and change detection of multi-temporal point clouds. Xi Yicheng[5] used the multi-temporal LiDAR point cloud data, and adopted the improved ICP matching algorithm and the surface thinning algorithm based on slope entropy to detect the change of urban structures, forming a 3D change detection of urban structures based on differential analysis. Fekete Anett[6] et al. use multi-temporal point cloud data to first fully automate the segmentation of vegetation (especially trees) in urban environments, and then determine and quantify change detection, which effectively divides and quantifies changes in trees. K. Zhou[7] et al. used ultra-high resolution (VHR) stereoscopic images for dense matching to generate 3D information. Compared with the LiDAR point cloud data, the change detection of urban buildings is carried out, and the urban 3D information is updated based on the LiDAR data, which has a good effect on the detection of small changes. Zeng Jingjing[8] et al. used the airborne LiDAR data of the two phases to first convert and register the data of the two phases, and then used the hierarchical clustering difference method to detect changes, which mainly detected the changes of urban land surface. Liu Yang[9] used the two-phase LiDAR point cloud data, used the principal component analysis of the tower spindle orientation method to realize the initial matching of the tower point cloud, and then improved the ICP algorithm to realize the registration of the two-phase point cloud, and finally realized the visual expression of the changing features.

In summary, there are more studies on the change detection of urban features based on point cloud data and image data, and less detection of changes in power transmission channel features. In this paper, a two-level matching method of multi-temporal point cloud data considering power transmission channel characteristics is proposed. The improved ICP algorithm is used to achieve rapid and accurate registration of point cloud data. Finally, the change detection of power transmission channel ground features is realized by classifying and comparing elevation differences.

2. ICP MATCHING ALGORITHM

ICP (Iterative Closest Point) was first proposed by Chen[10]and Besl[11] ,and it is a classical data matching algorithm. Its essence is based on the least square algorithm, through repeated iterative calculation of the feature points, to solve the optimal rigid transformation parameters, including translation, rotation, scaling and other parameters, so that the two sets of data unified in the same reference coordinate system. There is no scaling factor in the point cloud data studied in this paper, only

This contribution has been peer-reviewed.
https://doi.org/10.5194/isprs-archives-XLVIII-1-W2-2023-727-2023

translation and rotation coefficients are considered.and the mapping relationship is as follows:

$$\begin{bmatrix} x' \\ y' \\ z' \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\alpha & \sin\alpha \\ 0 & -\sin\alpha & \cos\alpha \end{bmatrix} \begin{bmatrix} \cos\beta & 0 & -\sin\beta \\ 0 & 1 & 0 \\ \sin\beta & 0 & \cos\beta \end{bmatrix} \begin{bmatrix} \cos\gamma & \sin\gamma & 0 \\ -\sin\gamma & \cos\gamma & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} + \begin{bmatrix} t_x \\ t_y \\ t_z \end{bmatrix} \quad (1)$$

Wherein, the rotation matrix can be expressed as:

$$R_{3x3} = \begin{bmatrix} \cos\beta\cos\gamma & \cos\beta\sin\gamma & -\sin\beta \\ -\cos\alpha\sin\gamma - \sin\alpha\sin\beta\cos\gamma & \cos\alpha\cos\gamma + \sin\alpha\sin\beta\sin\gamma & \sin\alpha\cos\beta \\ \sin\alpha\sin\gamma + \cos\alpha\sin\beta\cos\gamma & -\sin\alpha\cos\gamma - \cos\alpha\sin\beta\sin\gamma & \cos\alpha\cos\beta \end{bmatrix} \quad (2)$$

The translation matrix can be expressed as:

$$T_{3\text{x}1} = \begin{bmatrix} t_x & t_y & t_z \end{bmatrix}^T \quad (3)$$

Where, α, β and γ respectively represent the rotation Angle of a point along the x, y and z axes, and t_x、 t_y *and* t_z respectively represent the translation of a point along the x, y and z axes. 6 parameters of translation and rotation can be obtained by finding 3 groups of corresponding points with the same name. Several groups of points with the same name are usually selected to establish parametric equations to improve the accuracy of matrix transformation. The basic principle of ICP algorithm is to find the nearest point（p_i， q_i）respectively in the target point cloud P and source point cloud Q to be matched according to certain constraints, and then calculate the optimal matching parameter matrix R and T, so as to minimize the error function. The error function is as follows:

$$E(R,T) = \frac{1}{n}\sum_{i=1}^{n}\|q_i - (Rp_i + T) \quad (4)$$

Where n is the number of nearest point pairs, pi is a point in the target point cloud P, q_i is the nearest point corresponding to p_i in the source point cloud Q, R is the rotation matrix, and T is the translation matrix.

The specific steps of ICP algorithm are as follows:

(1) Take $p_i \in P$in the target point cloud P;

(2) Point out the corresponding points in the source point cloud Q $q_i \in Q$, makes the $\|q_i - p_i\| = min$;

(3) Calculate the rotation matrix R and the translation matrix T to minimize the error function;

(4) A rotation and translation transformation of p_i using the rotation matrix R and translation matrix T derived in the previous step gives the new set of corresponding points $p_i' = \{p_i = Rp_i + T,\ p_i \in P\}$;

(5) Calculate the average distance d between p_i' and the corresponding point q_i;

(6) If the average distance d is less than a given threshold or greater than the preset maximum number of iterations, the iterative calculation will be stopped. Otherwise, return to step 2 until the convergence condition is met.

3. IMPROVED ICP ALGORITHM FOR MULTI-TEMPORAL POWER TRANSMISSION CHANNEL POINT CLOUD MATCHING AND CHANGE DETECTION

3.1 Technology Roadmap

Using LiDAR point cloud data obtained at different periods, On the basis of ground feature classification, the improved ICP algorithm was used to register the data of the two periods, and then the key ground feature element categories were compared and analyzed. The changes of objects in the transmission line corridor were analyzed through clustering. The overall technical route is shown as the figure below (Figure 1).

3.2 Improved ICP point cloud registration algorithm

Power transmission channel feature types are complex, mainly dynamic feature vegetation, few features obvious, two periods of data changes greatly, increasing the difficulty and stability of point cloud data matching, Power transmission channel feature types are showed in Figure 2.

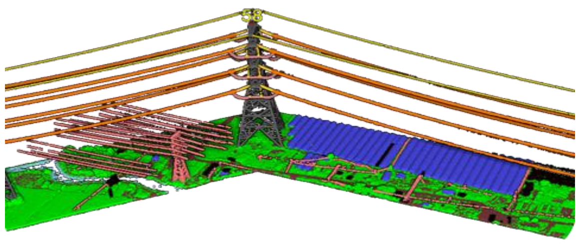


Figure 2. Power transmission channel

In order to avoid the influence of dynamic ground feature change information on the matching convergence process, this paper selects transmission tower (static ground feature) as the basic point cloud data for matching based on the classification of point clouds according to the characteristics of transmission lines. After obtaining multi temporal conversion parameters, it applies them to all kinds of point cloud data of the whole power transmission channel, and finally carries out change detection. According to the characteristics of transmission towers, a two-stage matching method from coarse to fine is proposed, i.e. firstly, coarse matching is carried out with the translation parameters of the central coordinate data of the two phases of towers; and then fine matching is carried out with the ICP algorithm based on point features according to the structure of coarse matching to obtain the conversion parameters. Defining the pre-stage point set as P and the post-stage point cloud set as Q, the specific improved algorithm process is as follows:

(1) Calculate the initial value of the average translation matrix T by using the center point coordinates of the two-phase tower (tower top) in the classification point cloud, namely:

$$\begin{cases} t_x = \frac{1}{n}\sum_{i=0}^{n}(x_i - x_i') \\ t_y = \frac{1}{n}\sum_{i=0}^{n}(y_i - y_i') \\ t_z = \frac{1}{n}\sum_{i=0}^{n}(z_i - z_i') \end{cases} \quad (5)$$

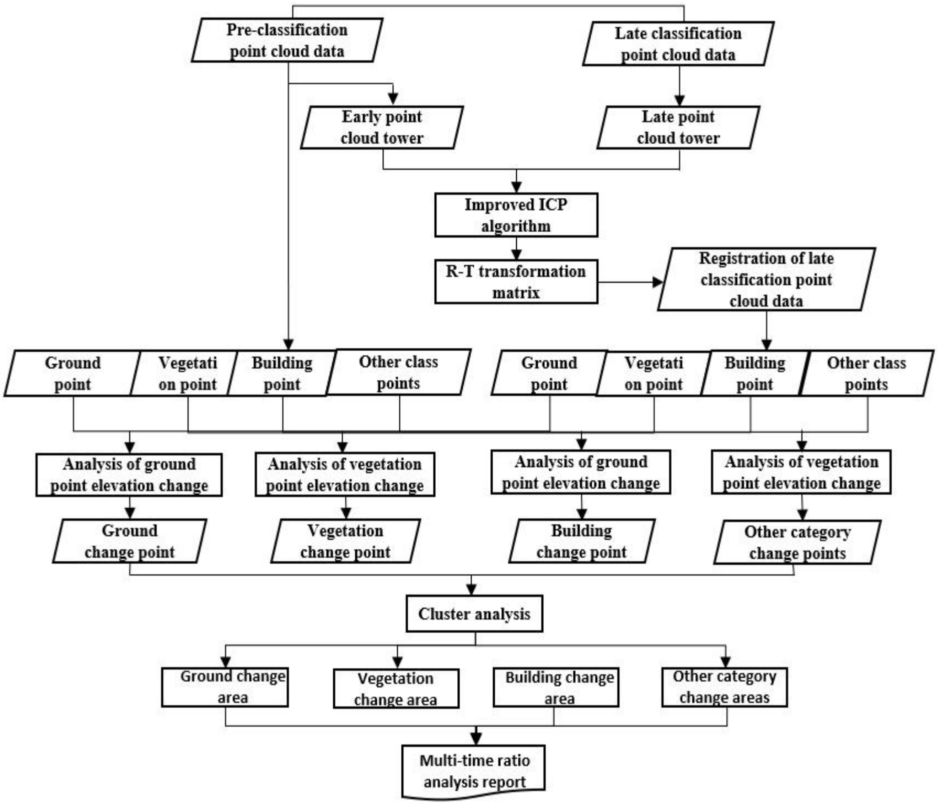


Figure 1. Technical route of the paper

(2) The Kd-tree was used to organize the early point swarm P to accelerate the search efficiency of discrete point cloud, and the Kd-tee is constructed by transforming the post-point cloud set Q by the mean translation matrix T to the point set Q'.

(3) Use the minimum value of the Euclidean distance between point pairs to determine the corresponding points, and remove point pairs whose Euclidean distance is significantly greater than a certain threshold to increase the proportion of correctly corresponding point pairs, improve the accurate transformation matrix, and ensure the accuracy of point cloud alignment.

(4) According to the determined point pair relation, SVD is used to solve the optimal rigid-body transformation parameter R-T which minimizes the objective function.

(5) Through iterative calculation, if the average distance d of the point set is less than a certain threshold value dth or greater than the preset maximum number of iterations n, the iterative calculation will be stopped.

(6) The transformation parameters are applied to the whole set of power transmission channel points for coordinate transformation registration.

3.3 Change detection method

This paper realizes change analysis based on the distance between points. Based on this, clustering is carried out on the changed point categories to realize object-based change detection. On the basis of the improved ICP algorithm registration, the point cloud categories of changes before and after were analyzed according to the ground object categories, and then the statistics of change categories and regions were realized based on the regional growth clustering algorithm, and finally the change detection report was generated.

The comparative analysis process of single category data change is as follows:

(1) Organize the pre-post point cloud dataset P and the transformed post-post data Q' using a Kd-tree.

(2) Finding a point set S within a certain distance r from the point to be judged.

(3) Calculate the height difference between the point to be judged and the points in the point set S. If the height difference value is greater than the given elevation threshold, the point cloud is a change point cloud.

(4) If the elevation of the point to be judged is greater than the elevation point within the point set, it is a new or long height point; if the elevation of the point to be judged is less than the elevation point within the point set S, it is a cut or deleted point.

On the basis of detecting change points, cluster analysis is carried out on point cloud data according to the category of point cloud based on the classified point cloud data, and change areas are detected according to the spatial location. The specific process is as follows:

(1) Find a point p in the point cloud, search for the nearest point using the Kd-tee algorithm, determine whether the distance from the adjacent point to the point p is less than a certain threshold r. If it is less, the point is put into the point set M and the point is removed from the original point cloud data.

(2) Select any point p from the point set M and follow

(3) step (1) to add points less than a certain threshold r to the set M until no new points are added, then M is a set of points in a changing region.

(4) Re-select points in the remaining point set and repeat steps (1) (2) to partition into a collection of n change regions by category.

(5) Clustering of the change point clouds for all categories following the 3 steps above.

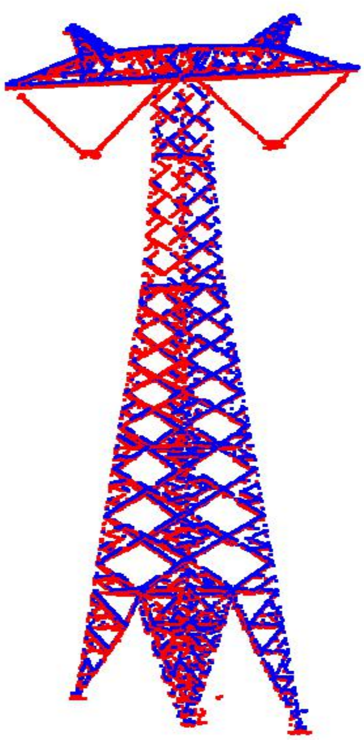
4. EXPERIMENTAL ANALYSIS

4.1 Experimental data

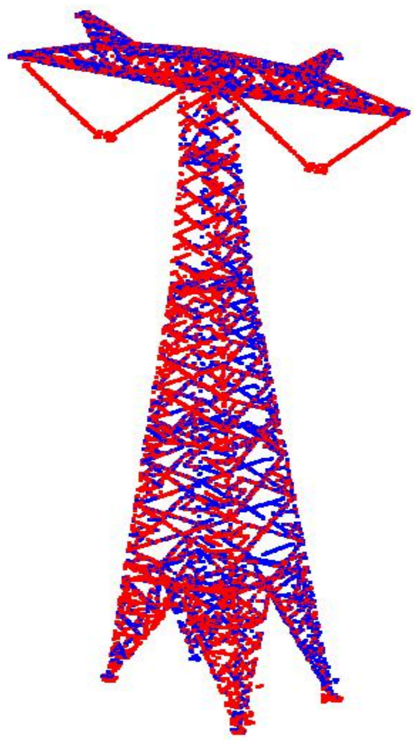
The experimental data was selected from the laser scanning data of a ±800kV EHV transmission line collected by State Grid Electric Power Space Technology Co,Ltd. in 2014 and 2020 respectively. The scanners used for the experiment were Riegl VQ-480 and Riegl VUX-LR, and the point density collected was about 50 points/m2. The point cloud data of the two phases were classified, including poles, guide lines, vegetation, ground, roads, railways and cross-over power lines, etc. The 2014 data was used as the baseline data and the 2020 data as the data to be aligned.

4.2 Experimental results and analysis

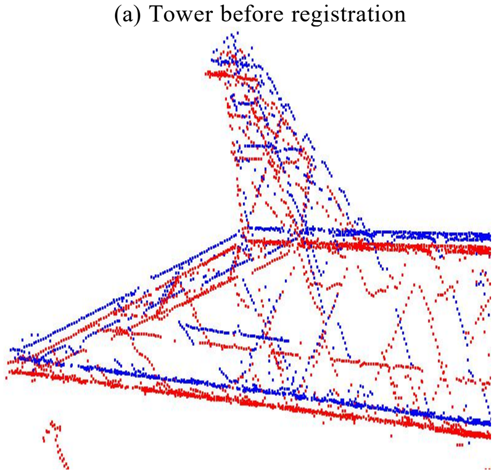
The comparison diagram of tower point cloud after matching with improved ICP algorithm is shown in Figure 3 below. In the figure, the blue point cloud is the baseline data in 2014, and the red is the point cloud data in 2020. The difference between the point clouds before the tower matching is about 0.3~0.5m, and the difference between the point cloud data after the tower matching is about 0.05m.



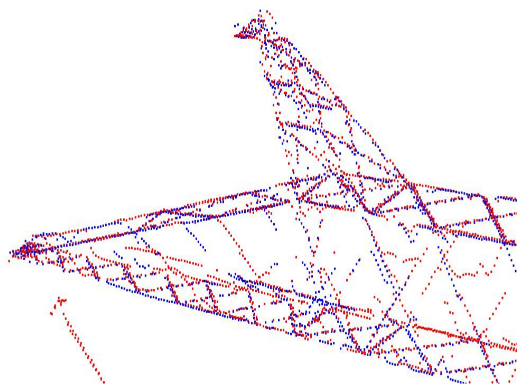
(a) Tower before registration



(b) Tower after registration



(c) Tower corner before registration



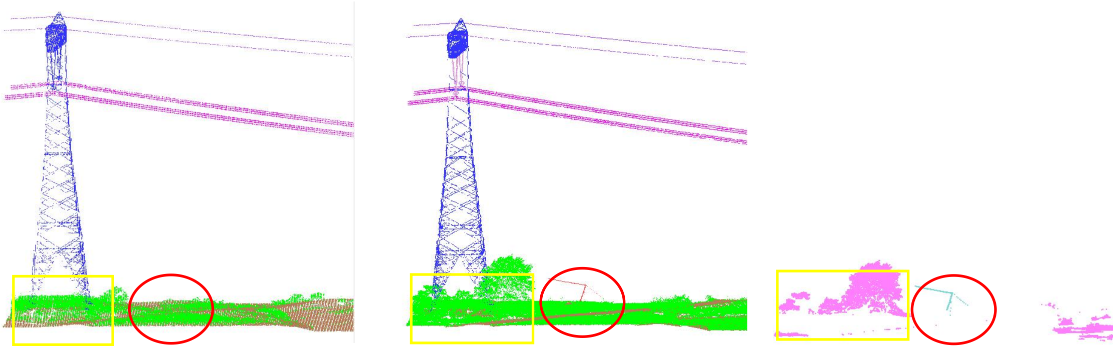
(d) Tower corner after registration

Figure 3. Overlapping of power tower in two phases after registration (a) The whole tower before registration ; (b) The whole tower after registration; (c) The tower corner before registration; (d) The tower corner after registration.

https://doi.org/10.5194/isprs-archives-XLVIII-1-W2-2023-727-2023

4.3 Change detection effect diagram

After matching, the point cloud data is checked for changes and the parameters are set as follows: high vegetation with a search radius of 5m and a height change value of 5m; buildings with a search radius of 5m and a height change value of 3m; roads with a search radius of 5m and a height change value of 3m; and crossings with a search radius of 5m and a height change value of 3m. The results of the change detection are shown in Figures 4, 5 and 6 below, with the point clouds displayed by classification category.

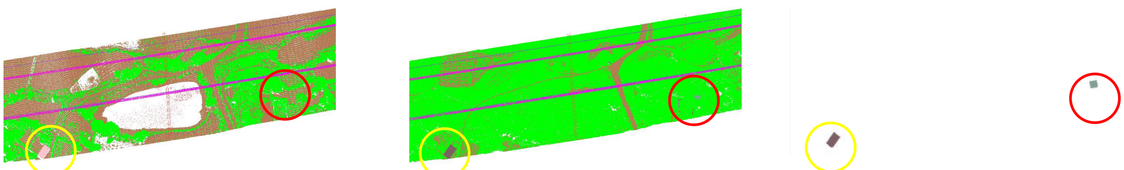


(a) data in 2014 (b) data in 2020 (c) change object

Figure 4. Cross line change detection (a)The graph shows data for 2014, with green dots for vegetation; (b) The graph shows data for 2020, with green for vegetation, and the yellow rectangular box shows that the trees have grown over six years, with a significant change in height, and a new crossing span next to the pole tower in 2020; (c) The graph shows the results of the change detection, with the pink dots indicating the changed vegetation (inside the yellow rectangular box) and the blue dots showing the new crossing span (within red circles).

(a) data in 2014 (b) data in 2020 (c) change object

Figure 5. Change area of the road (a) In the figure is the data of 2014, the green points are vegetation, the yellow rectangle area is the land surface without new roads, green is vegetation points; (b) The figure shows the data in 2020, green is vegetation, and the yellow rectangular box is the newly added lines; (c) The figure shows the result of change detection. The pink dot represents the vegetation growing taller, the rectangular box represents the new line, and the dark green represents the vegetation felled due to the new line.



(a) data in 2014 (b) data in 2020 (c) change object

Figure 6. Change area of the building (a)The graph shows 2014 data, the pink dots in the yellow circles are buildings and no buildings are seen in the red circles; (b) The graph shows 2020 data, no buildings in the yellow circles are ground level dots and there are building dots in the red circles; (c) The graph shows the results of change detection, the yellow circles indicate demolished buildings and the red circles indicate new buildings.

It can be found in Figure 4, Figure 5 and Figure 6 that on the basis of data matching between the two phases, changes in buildings, vegetation, roads and crossing lines of transmission line corridors can be effectively detected through comparative analysis of different categories of clustering.

5. CONCLUSION

This paper presents a technology flow of power transmission channel change detection. In order to avoid the influence of the change information data of dynamic ground features of power transmission lines on the matching of two-phase point cloud data, based on the classification of point clouds, this paper proposes a two-level matching method of multi-temporal point cloud data that takes into account the characteristics of power transmission channels to achieve accurate registration of point cloud data, and then conducts change detection and analysis of point cloud data of different types of ground features through elevation difference. The clustering algorithm based on region growth can realize the statistics of change categories and regions, and realize the change detection of power transmission channel ground objects. This technique provides a reference for power transmission line change detection. Experiments show that this method can effectively detect the change of power transmission channel crossing lines, buildings, vegetation, roads, etc.

ACKNOWLEDGEMENTS

We gratefully acknowledge the financial support of the National Natural Science Foundation of China Youth Project (42104017); The Pyramid Talent Training Project of Beijing University of Civil Engineering and Architecture (JDYC20220825); The Young Teachers' Scientific Research Ability Promotion Plan Funding of Beijing University of Civil Engineering and Architecture(X21021).

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