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Automatic Multi-source Data Fusion Technique of Powerline Corridor using UAV Lidar

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***Abstract*—With the increasing scale and complexity of powerline construction, the challenges of powerline system operation and maintenance are gradually increasing. The research and application of unmanned aerial vehicle (UAV) Lidar technology for powerline inspections is developing rapidly. The Lidar point cloud and visible light measurement are processed intelligently by the powerline multi-source and heterogeneous data automatic fusion technology. Then the three-dimensional model of the powerline system and electrical equipment is obtained. Consequently, the efficient resolving of point cloud data for powerlines, identification of equipment locations and types are realized. The fast measurement and elaborating modeling of the three-dimensional system for powerlines is obtained, which may effectively and comprehensively show the operation status of powerlines. The point cloud classification algorithm is adopted in this paper. Experimental results demonstrated that the proposed method performed well in the detection accuracy of identification and classification of lines and pylons in a complex environment. The classification accuracies for transmission lines and distribution lines are 97.26% and 95.29% respectively. The average classification accuracies of both lines and pylons are 80.88% and 82.25%, respectively.**

Keywords*—*powerline system, UAV Lidar, multi-source data fusion, point cloud, three-dimensional model

I. INTRODUCTION

Overhead powerlines are one of the central equipment in the power grid. Therefore, the safe operation of overhead powerlines is very important for power system. In order to guarantee that the overhead powerline is in a safe and reliable operation state at any moment, the equipment maintenance department needs to conduct regular inspections to detect and eliminate anomalies beforehand [1]. Traditional manual inspection is time- and labor-consuming, and it is hard to find the defects and anomalies of powerlines without delay. In recent years, inspections by UAVs are used to replace traditional manual inspections and become the main inspection method by its high-tech and automated equipment gradually [2].

Lidar technology can achieve rapid acquisition of large-scale multidimensional terrain and object data which is of high precision and highly automated. Lidar is suitable for rapid generation of digital surface model (DSM), digital elevation model (DEM) and digital orthophoto map (DOM). The specific advantages of Lidar technology are non-contact and active measurement, high resolution and high density, strong anti-active interference ability, and good low-altitude detection performance. It also has vegetation penetration ability and can detect the real terrain on the surface more accurately. The processing of point data acquired by Lidar is actually to classify and extract multi-dimensional and complex data [3]. The point cloud classification of overhead powerlines is the process of identifying powerlines, pylons, vegetation, buildings and other target objects from the original data. For the classification and extraction of target objects, three directions can be identified including vegetation (buildings), lines, and pylons. For the point cloud classification of vegetation or buildings, there are two methods. One is based on the difference of point cloud data features between surface points and non-surface points in space [4]. The other is based on point cloud segmentation [5], triangle mesh method [6] and other filtering strategies for algorithm extraction. While for the point cloud data classification of powerlines there are methods based on dimensional and directional features of powerline data segmentation [7], Hough transform methods [8], statistical analysis and 2D image processing [9]. For the extraction of pylon point clouds, most of the classification extraction methods are based on multi-dimensional feature analysis of two-dimensional grids [10]. In recent years, artificial intelligence technology has been applied to point cloud data processing, which effectively improve the classification efficiency. For example, deep learning methods can directly use the original point cloud as input and retain the 3D information of the point cloud fully. Then the features of 3D scenes or objects are extracted [11]. This paper has significant contributions to show the use of UAV data to help smooth running of our society with practical examples. Also, it has tutorial values in explaining the current work done in data fusion techniques used in smart energy environment. The paper is organized as follows. Section II explains UAV Lidar 3D scanning. Section III describes data processing and some scenarios example found in real-life. Section IV demonstrates a case for defect analysis fusion technique based on fusion data; Section V gives conclusions and some future work.

II. UAV LIDAR 3D SCANNING

A. Multi-source state data collection process of powerline

According to the requirements, set up calibration fields, monitor radars and cameras. The flight speed is determined according to the point cloud density, accuracy requirements, terrain fluctuations, laser frequency, etc. The flight is designed based on the feasibility study of the route or the survey documents after the preliminary design review. According to the principle of GPS base station site selection, combined with the results of geodetic control measurements, a point suitable is selected for the layout of the control point as the base station location. After the Lidar system and the base station are in place, the Lidar system starts, and the base station receives information normally. The Lidar parameter setting is checked for correctness, then the UAV takes off to collect data.

B. *Unified access to multi-source state data*

It is necessary to study the automatic data fusion technology according to the characteristics of multi-source and heterogeneous data of powerlines. The 3D laser point cloud data obtained by UAV lidar is in LAS format, which includes 3D coordinates (X, Y, Z), multiple echo information, intensity information, scanning angle, classification information, flight zone information, and flight attitude information, project information, GPS information, data point color information, etc.

For different data sources (including various monitoring devices, UAV patrol data, operation and maintenance data, etc.), corresponding data interface schemes and protocols are designed and formulated. Research and develop a unified access platform for multi-source data to complete multi-source data access.

III. DATA PROCESSING

A. *Point cloud data denoising*

In point cloud data denoising, the standard deviation of the average distance is calculated by determining the adjacent points and calculating the distance between each point and its adjacent points. Points outside the minimum allowable deviation range of the average distance are regarded as noise points.

B. *Automatic filtering of surface points*

In order to obtain a digital surface model, it is necessary to identify surface data and non-surface data, then perform filtering and classification of point cloud data to obtain surface point clouds automatically. A filtering algorithm based on an irregular triangulation net is adopted in this paper. At first, the algorithm divides the inspection area into several blocks, selects the lowest point of each block in the inspection area as the seed, and uses it to construct an initial triangulation net, which represents the rough topography of the inspection area. Then, according to certain criteria, other laser foot points are identified. The points that meet the criteria are inserted into the triangulation net, and the triangulation net is optimized to reveal the terrain of the inspection area more accurately. The triangulation net is updated by calculating the distance and angle from the laser point to the corresponding triangle. This filtering algorithm is based on the original point cloud data directly, no accuracy loss caused by interpolation, and can apply to data with different point densities.

By selecting the point cloud data and categories that participate in the classification of surface points, automatic filtering is performed, the maximum building size and the maximum terrain slope are mainly considered for parameter setting. For areas with sudden elevation changes, parameters or algorithms are adjusted to re-classify small areas automatically, and re-classify points that are misplaced by manual editing. The classification results are checked by tools such as translation and rotation. If there is an obvious classification error, it needs manual refined classification again.

C. *DEM/DSM data generation*

After point cloud filtering, the surface points generate the DEM results of the Digital Terrain Model by interpolating and gridding regularly. The appropriate grid size and interpolation method are selected to give the output path of the file to generate DEM data.

D. *Point cloud data classification*

The purpose of point cloud classification is to mark the obtained original laser point cloud as surface points, vegetation points, building points, power line points, pylon points, etc. In this paper, by considering the actual needs of power grid dangerous point detection, a deep learning-based point cloud classification method is proposed as shown in Fig. 1 below.

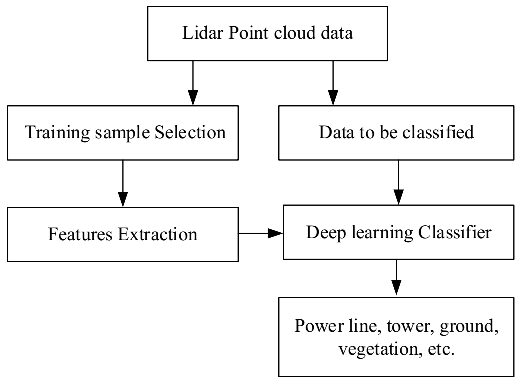

Fig. 1. Flow chart of point cloud classification algorithm

Select training samples from original lidar point cloud data of power lines manually. In order to ensure the accuracy of the classification, different pylon types and line types should be considered when selecting. The power line and pylon categories should be manually chosen, and the surface points should be decided by filtering algorithm.

For power lines, the Hough straight line detection algorithm is generally used, which can be less disturbed by discontinuous points and overcome the discreteness of power line data. The tower is a clustered point group, and the erosion operation is adopted to eliminate the boundary of the transmission line. The expansion operation is employed to obtain the connected area. For each point, point cloud classification algorithm determines its neighbor points to calculate features, which includes the four following methods such as K neighborhood points, spherical neighborhoods, cylindrical neighborhoods, and grid neighborhoods.

The K neighborhood points computed features are as follows. By constructing covariance matrix for each point and its K neighborhood points, the eigenvalue λ_i is calculated according to the covariance matrix, where i=1, 2, 3. And the following features are calculated based on the eigenvalue.

$$\text{Sum} = \lambda_1 + \lambda_2 + \lambda_3 \tag{1}$$

$$\text{Omnivariance} = \sqrt[3]{\lambda_1 \cdot \lambda_2 \cdot \lambda_3} \tag{2}$$

$$\text{Eigenentropy} = -\sum_{i=1}^{3} \lambda_i \cdot \ln(\lambda_i) \tag{3}$$

$$\text{Anisotropy} = \frac{\lambda_1 - \lambda_3}{\lambda_1} \tag{4}$$

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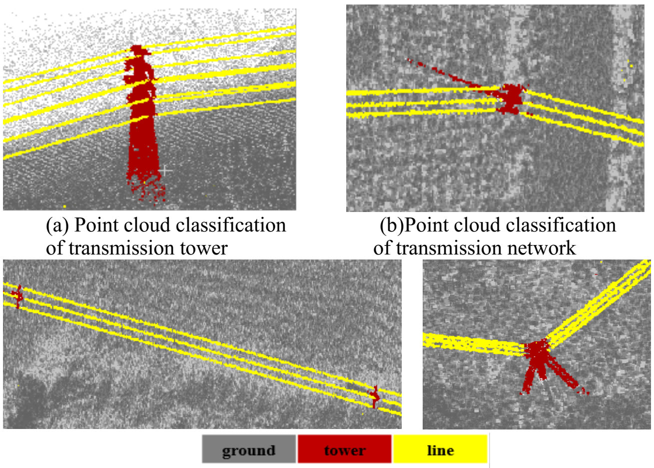
$$\text{Planarity} = \frac{\lambda_2 - \lambda_3}{\lambda_1} \tag{5}$$

$$\text{Linearity} = \frac{\lambda_1 - \lambda_2}{\lambda_1} \tag{6}$$

Data classification methods develop classifier based on feature extraction. And the unclassified data classify automatically by this classifier. The classified results include surface point, power line, pylon, etc. Speckle merge was performed on the automatic classification results and optimized according to the characteristics of the power line itself. Remove misclassified data according to pylon location file. By setting the threshold, only points within the appropriate distance from surface points can be considered on the power line, and this eliminates misclassified points. Isolated noise points are removed according to neighborhood statistics as shown in Fig. 2 below.



(a) Point cloud classification of transmission tower

(b)Point cloud classification of transmission network

(c)Point cloud classification of straight line

(d)Point cloud classification of corner

Fig. 2. Point cloud classification model in different scenarios

The intersection over union and classification accuracy of point cloud data is shown in Table I and Table II, which includes distribution line corridor with complex backgrounds. Combined with the big data carrying capacity, the automatic powerline and pylon classification is performed, with the average classification time of each span less than 20 seconds. The classification accuracy of lines is 97.26% and 95.29%, and the average classification accuracy of both lines and pylons is 80.88% and 82.25%, respectively.

TABLE I. INTERSECTION OVER UNION IN DIFFERENT SCENARIOS

	Intersection Over Union of Towers	**Intersection over Union of Lines**	**Average Intersection over Union**
Transmission Line Corridor	62.91%	97.26%	80.09%
Distribution Line Corridor	63.94%	95.29%	79.62%
Straight Line Pylon	64.73%	96.56%	80.65%
Corner Pylon	63.60%	95.71%	79.66%

TABLE II. CLASSIFICATION ACCURACY IN DIFFERENT SCENARIOS

	Accuracy o f Towers	**Average Accuracy**
Transmission Line Corridor	63.77%	80.88%
Distribution Line Corridor	69.40%	82.97%
Straight Line Pylon	66.93%	82.25%
Corner Pylon	72.63%	85.18%

In practical applications, select the powerline corridor point cloud data containing a complete span of powerline and its pylon. Classify pylon, earth conductor, vegetation, and so on manually. And save the classification results as a deep learning training model. The point cloud classification effect using PointNet++ deep learning algorithm is shown in Fig.3., and the point cloud includes different voltage level and complex powerline corridor. The figure shows that the point cloud classification of powerlines based on deep learning can accurately classify the lines, pylons, surfaces and vegetation of different voltage levels with relatively high accuracy.

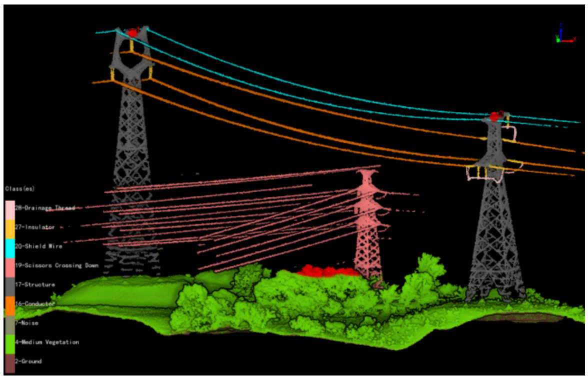


Fig. 3. Powerline point cloud classification based on deep learning

E. Line data vectorization

In laser scanning point cloud processing, the 3D modeling of pylons and lines is also called 3D vectorization of pylons and lines, which is an advanced formation of geographic information data. By automatically vectorizing multiple lines and improving manually, the vector model of 3D transmission lines is mass-produced, and can be edited later.

The vectorization solution is based on the detection of powerline conductors and pylons fitting models from the laser point cloud, and its accuracy depends on the preparation of the laser point cloud data and the density of the point cloud. High density laser point cloud (more than 10 points per square meter) may create a more accurate real-world three-dimensional model of the powerline as shown in Fig. 4. And it can also represent the details of the pylon and conductor structure.

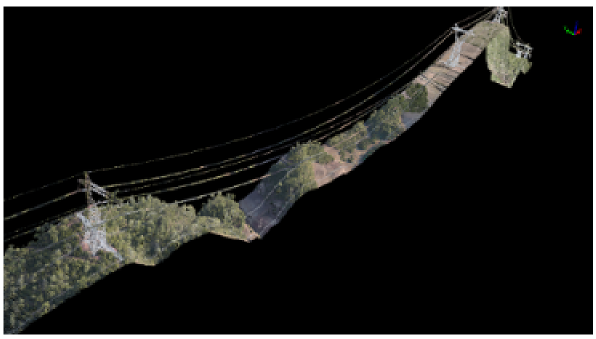


Fig. 4. Powerline data fusion

IV. DEFECT ANALYSIS FUSION TECHNIQUE BASED ON FUSION DATA

Through the aforementioned process, the point cloud is classified into surface points, vegetation points, building points, powerline points, pylon points, etc. Through

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vectorized lines, traverse the point cloud data of trees, buildings, crossing points is traversed, and calculate the shortest distance from the line and the distance between the lines is calculated. By comparing with safe operation requirements, an alarm of dangerous objects is given if needed.

A. *Integrated inspection strategy*

The UAV Lidar measurement system was used to obtain the high-precision point cloud of the line corridors, the visible light stereoscopic measurement was used to obtain the 3D real data of the line corridor, and the 3D model of the line corridor, the orthographic images of the top surface and the elevation of the line corridor were generated through the unified coordinate system. To realize the effective identification and extraction of trees and obstruction in the corridor, a tree and obstruction assessment report was generated. The evaluation report can effectively transform qualitative tree obstruction analysis into quantitative analysis, and calculate the location of trees to be felled in the corridor and calculate their felled area, so as to ensure the safe operation of the corridor. The technical flow chart of the fusion process of UAV lidar data and visible light stereoscopic measurement data is shown in Fig. 5.

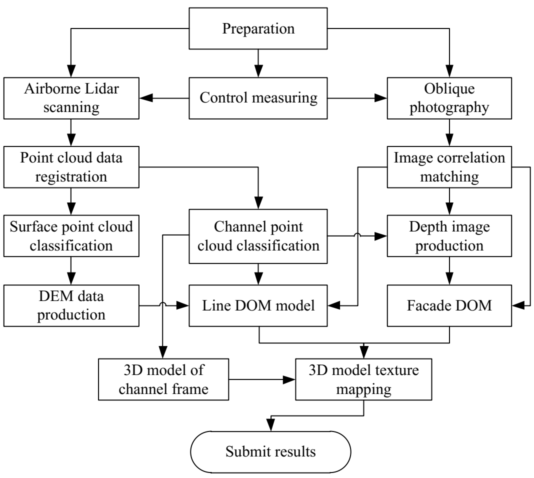

Fig. 5. Flow chart of data fusion process

B. *Multi-service real scenario integration display*

Based on the massive 3D laser classification point cloud data after data processing and analysis, the visible light image/video data, infrared image/video data, multi-spectral image, etc. on the server are integrated as shown in Fig. 6. By constructing a high-precision powerline digital corridor, which enhances the dynamic monitoring of line assets. It optimizes the asset allocation of the power industry while reducing the construction cost of powerlines, and it comprehensively improves the practice of line asset management in modern power enterprises.

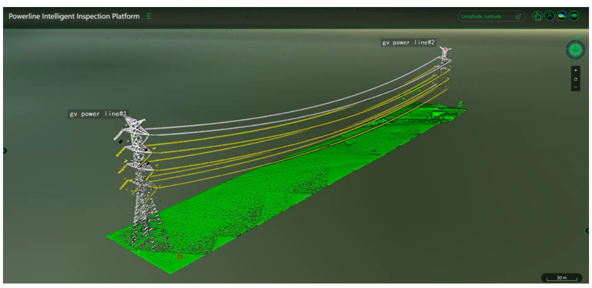

Fig. 6. 3D panoramic display of powerline corridor

V. CONCLUSIONS

The application of UAV Lidar intelligent inspection technology can improve the efficiency of power inspection. In the inspection, intelligent processing is carried out by using Lidar point cloud and visible light measurement to realize defect detection and analysis, fast measurement of 3D corridors, refined modeling and all-round display, and integrated display and deepened application of real business scenarios. The data processing and deepening application introduced in this paper has a good performance, improving the intelligent operation and maintenance of powerlines effectively. This work can make a positive contribution to reduce disasters such as fire due to the discovery of damaged power equipment in a much earlier stage. Needless to say, this is important to smart city deployment and advancing living standard of people. In the future research, the method will be further optimized from the perspective of real-time online monitoring data access and fusion display timeliness, so as to improve the powerline inspection. Also standards development needs to be considered for interoperability within various countries.

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