International Journal for Housing Science and Its Applications
Publish August 4, 2025. Volume 46, Issue 3 Pages 2449-2459

https://doi.org/10.70517/ijhsa463204

Fine Optimized Segmentation Model for Insulator Point Cloud of Power Generation Tower Based on Point Network + LSTM

Chao Gao[1,*], Yongquan Wu[2], Zheng Huang[3], Siwei Zhang[2], Tao Long[2] and Xinhou Liu[2]
[1] State Grid Jiangsu Electric Power Co., Ltd., Nanjing, Jiangsu, 210024, China
[2] Nanjing Power Supply Branch of State Grid Jiangsu Electric Power Co., Ltd., Nanjing, Jiangsu, 210024, China
[3] JiangSu Frontier Electric Technology Co., Ltd., Nanjing, Jiangsu, 210024, China
Corresponding authors: (e-mail: Dzg3567@163.com).

Abstract Due to the varying reflectivity of LiDAR scanning small targets on insulators at different positions, the point cloud granularity exhibits irregularity and disorder. Using conventional linear learning methods for point cloud segmentation of insulator small targets results in unreasonable segmenta-tion granularity and significant segmentation errors. Therefore, this paper proposes a point cloud subdivision optimization model for power tower insulators based on point network+LSTM. A classification network for insulator positioning timestamp data was constructed using a point network, and each point cloud feature was extracted using MLP to address the impact of irregu-larity and disorder in the point cloud on segmentation rationality. Utilizing the symmetric function MaxPooling network for secondary extraction of point cloud features, achieving three-dimensional coordinate displacement invariance with increased point cloud data volume. Remove interference from point cloud data outside the range through direct filtering and cloth filtering algorithms. Uti-lizing the nonlinear learning ability of LSTM network to improve the data dependency problem of RNN network. By iteratively training granularity through granularity multiplication, the rationality of point cloud data segmentation granularity can be improved. Establish a point cloud data seg-mentation model for power tower insulators based on LSTM network, and introduce a loss function to optimize it, in order to reduce the segmentation error of insulator small targets. The experimental results show that after the application of this method, it still maintains high segmentation confi-dence when the amount of point cloud data of power tower insulators increases. The fine-grained rationality of point cloud data segmentation is strong, and the average absolute error of segmen-tation is small, less than 0.1%, and it can preserve the details of the original data. This method can improve the reliability of point cloud subdivision of power tower insulators, with good subdivision effect, and provide reference for the classification and classification of insulator states.

Index Terms pointnet, LSTM, Power tower, Insulators, Point cloud, Optimize segmentation, Pass through filter

I. Introduction

Power tower insulators are components used to support and fix busbars and live conductors, and to ensure sufficient distance between live conductors or between conductors and the ground to ensure insulation [1], [2]. However, due to the long-term exposure of insulators to outdoor environments and the influence of natural factors such as wind, sun, rain, and snow erosion, the surface of insulators is prone to accumulate impurities such as dust and dirt. These impurities can conduct electricity under humid conditions, thereby reducing the insulation performance of insulators and even causing flashover accidents [3]-[5]. By accurately detecting and timely replacing insulators, power accidents caused by insulator failures can be effectively prevented, ensuring the safety of people's lives and property [6], [7]. Therefore, how to accurately detect anomalies in insulators to ensure timely detection and handling of potential problems has become a current research hotspot.

Reference [8] used unmanned aerial vehicle (UAV) to capture insulator image data over high-voltage lines in the suburbs of Opole, Opolski Province, Poland. The point set on the insulator image was determined, and the color intensity distribution lines were drawn to connect these points. The Periodogram method was then used to convert the configuration file, and finally the XGBoost algorithm was used to classify and detect power tower insulators. This method effectively suppresses complex background interference through frequency domain feature extraction, improving detection robustness in dynamic environments. However, this method overly relies on the characteristics of color intensity distribution and is easily affected by factors such as lighting changes and device color differences, making it prone to failure in low contrast scenes. Reference [9] proposed a privacy preserving insulator detection method based on federated learning. By constructing a dataset for insulator fault detection and training convolutional neural network (CNN) and multilayer perceptron (MLP) models within a federated learning framework for insulator fault detection, the risk of data leakage is reduced by 70% while ensuring detection accuracy (F1 ≈ 0.93). However, the disadvantage of this method is that it is prone to poor segmentation detail recognition during the training process, resulting in insufficient accuracy in insulator anomaly detection. Reference [10] designed a deep learning based algorithm for detecting insulator faults in transmission lines. The algorithm used drones to collect aerial images of insulators in different scenarios, established a dataset of insulator faults, and enhanced the robustness of the algorithm. By combining the gam attention mechanism to improve the YOLOV9 algorithm, channel pruning and knowledge distillation were used to reduce the model's parameter count by 40% and increase detection speed by 25% (Tesla T4 GPU). This successfully improved the algorithm's feature extraction ability for insulator faults at a lower computational cost; However, the non-linear learning ability of this method in insulator fault detection is relatively low. The reference [11] studied the application of an improved YOLOv5 algorithm in insulator fault detection. On the basis of the original heavy image lightweighting, the channel data suitable for insulator detection has been improved. By reconstructing the channel redundancy strategy, the channel importance weight can be adaptively adjusted according to the texture features of the insulator, and the ability to extract fine-grained features can be enhanced. However, the small target detection performance of this method is limited, and the detection and segmentation accuracy of long-distance small target insulators is insufficient.

Based on the research method, this paper proposes to design a fine optimization segmentation model of power tower insulator point cloud based on pointnet+LSTM. The technical route of this paper is as follows:

(1) The spatial three-dimensional coordinates, echo times and echo intensity in-formation of power tower insulator point cloud data and the characteristics of point cloud data are analyzed;

(2) In response to the irregularity and disorder of the original point cloud, this paper innovatively uses PointNet network to construct a insulator positioning timestamp data classification network, and designs a solution corresponding to the above characteristics: firstly, using MLP to extract features for each point, avoiding the influence of irregularity in the point cloud. The input data to the network consists of the original three-dimensional coordinates and additional features of each point (color, normal vector, etc.), without tedious preprocessing. The second is to use the symmetric function MaxPooling to extract the features of each point, ensuring that the obtained results are independent of the order of point inputs, thus achieving permutation in-variance. Remove the power tower insulator point cloud data that is not within the value range through the direct filter and cloth filter algorithm, and preprocess the power tower insulator point cloud data;

(3) In response to the problems of poor non-linear learning ability and fi-ne-grained segmentation in existing methods, this paper innovatively utilizes the ex-cellent long-term memory function and non-linear learning ability of LSTM network to improve the data dependency problem of RNN network, and determines the forget gate for important information memory of insulator three-dimensional reflection data. During the training process, continuously update the point cloud segmentation data of power tower insulators, multiply the old state with the current granularity, and re-move some unnecessary information to improve the granularity of power tower insu-lator point cloud data segmentation. Build a point cloud data segmentation model for power tower insulators based on LSTM network, and introduce a loss function to op-timize it, reducing the segmentation error of insulator small targets.

II. Design of fine optimization segmentation model for insulator point cloud of power tower

II. A. Data feature analysis of power tower insulator point cloud based on scanning reflectivity

In practical applications, the spatial three-dimensional coordinates, echo frequency, and echo intensity information in point cloud data are most commonly used [12], [13]. The spatial three-dimensional coordinates, echo information, and corresponding scanning information in the insulator positioning timestamp data constitute the point cloud information of the insulator of the power tower. Therefore, based on the data recorded by the POS and laser rangefinder of the system, this article calculates the three-dimensional spatial coordinates of the insulator positioning timestamp data [14], [15]. The specific conversion formula for different coordinate systems is:

$$\overline{X_G} = \overline{X_O} + R_y + P_G + R_i \begin{bmatrix} 0 \\ x \\ y \end{bmatrix} \tag{1}$$

In the formula, (x, y) represents the spatial coordinate point of insulator positioning timestamp data, and $(X / R / P)$ represents the three-dimensional spatial coordinate point.

In the process of obtaining the time stamp data of insulator positioning, the three-dimensional coordinates are obtained through the laser radar system, and the reflection intensity information from the power tower insulator is recorded at the same time. The response of ground objects to laser signals is often reflected by the intensity of laser signals, and the measurement methods used by different lidar systems are completely different. Due to the different materials of different ground objects, the intensity signals of the laser will also have different degrees of difference. The reflection coefficient of the ground environment to the laser is usually reflected by the wavelength, the light and darkness of the medium surface, etc. [16]. The reflectivity will increase with the increase of the brightness of the medium surface. In the laser reflection of the power tower insulator, the intensity signal of the laser reflects the reflectance of the ground object, but it can not be used to reconstruct the reflection characteristics of the ground object. The main reason is that in addition to the important role of the reflective medium, its incident power, pulse generation time and distance to produce atmospheric absorption laser and other factors also play an important role.

The time stamp data of insulator positioning obtained by airborne lidar system are distributed discretely, which is mainly caused by different scanning methods and surface characteristics [17]. The interference factors of airborne lidar scanning are complex, which makes the point cloud data density obtained in different regions inconsistent. In the post-processing of the time stamp data of insulator positioning, the time consumption is long due to its scattered, lack of relationship between points and invalid organization. In addition, different scanning methods of the scanner during operation may also lead to different densities of time stamp data for insulator positioning in different positions, resulting in uneven data distribution in the scanning band, which is another feature of the point cloud data form. If the data is unevenly distributed, one of the reasons for this phenomenon may be the point cloud hole, that is, the phenomenon of blocking by tall objects such as the side of buildings, resulting in the part without laser points even in the data set.

Generally, the measurement index of each acquisition point generated by the laser radar pulse is called the intensity, which reflects the reflectivity expression of the wavelength in the form of a function. Because the reflectivity is formed by the laser signal on the surface of the object, the echo intensity will change due to the different surface of the object. The spectral information in the image is similar to the intensity information, so the echo intensity plays an indispensable role in the filtering and classification of lidar insulator positioning timestamp data. Table 1 shows the reflectivity of power tower insulator point cloud laser signal under the influence of various media.

Table 1: reflectivity of different media.

material quality	reflectivity/%
building materials	75
Regular trees	94
Needlelike tree	30
sand	50
Concrete floor	24

II. B.Global feature extraction of insulator 3D point cloud based on timestamp PointNet

According to the analysis in the previous section, the original point cloud data has the characteristics of irregularity and disorder, making it difficult to perform reasona-ble granularity division. Meanwhile, in voxel segmentation of point cloud data, two-dimensional projection permutation can lead to the loss of three-dimensional fea-ture information of the point cloud of power tower insulators [18], [19]. In response to the irregularity and disorder of raw point cloud data, this paper innovatively con-structs an insulator positioning timestamp data classification network using point cloud networks. Use MLP to extract features (color, normal vector, etc.) for each point, avoiding the impact of irregularity and disorder in the point cloud on segmentation. Using the symmetric function MaxPooling to extract the global features of each point in a quadratic manner ensures that the obtained results are independent of the order of point inputs, thereby achieving permutation invariance in the three-dimensional in-formation space and solving the problem of three-dimensional information loss.

For irregular point cloud data, PointNet uses MLP to extract features and upgrade dimensions of each input point. Each point is mapped from the original three-dimensional space to the 1024 dimensional redundant space, and then the maximum value is extracted using the symmetric function MaxPooling. Then, Max-Pooling is performed on all points mapped to 1024 dimensions to obtain global features. Then a network is used to further digest the global features and get the point cloud feature classification results.

Among them, layer h is the feature mapping layer, which is responsible for mapping each point to the high-dimensional feature space; Layer g is the MaxPooling layer of symmetric operation, which is responsible for extracting the maximum value of high-dimensional features mapped from each spatial coordinate point (x,y); p-Layer digests MaxPooling to obtain global features of insulator 3D reflection data.

In the feature classification of insulator 3D reflection data, the network extraction formula of PointNet is:

$$f(x_1, x_2, \ldots x_n) = p \times g(h(x_1), h(x_2), \ldots h(x_n)) \tag{2}$$

The intermediate features of insulator 3D reflection data are transformed, that is, the transformation matrix generated by another spatial transformation network T-Net is used to transform the features mapped to high dimensions. However, the transformation matrix of high-dimensional feature space has higher dimensions than the transformation matrix of spatial coordinate point (x, y), and the optimization is more difficult. Therefore, the training loss regularization loss formula is introduced to solve this problem, namely:

$$\eta_i = \left\| V - B^T \right\|_F^2 \tag{3}$$

In the formula, V is the extracted feature alignment matrix, B represents the regularization loss, and F and B represent the constraint conditions respectively. The feature alignment matrix can be constrained into an orthogonal matrix, and the orthogonal change will not lose information.

It is necessary to combine the two transformed networks with PointNet to get the insulator 3D reflection data feature classification network. The input insulator 3D reflection data features are transformed by 3 × 3 to obtain the aligned point cloud in 3D space, and then projected to the 64 dimensional space. The 64 dimensional space data are more normalized by another transformation on this spatial dimension. Then the 64 dimensional features are gradually mapped to the 1024 dimensional space using MLP, and then the maximum eigenvalue of each point is mapped to the 1024 dimensional space using the symmetric function MaxPooling, followed by a fully connected network to achieve classification [20]. Due to the disorder of the characteristics of the three-dimensional reflection data of insulators, there are generally three ways to adapt to this characteristic: sorting the input data through the sorting function, aggregating the characteristics through a symmetric function, and taking the input data as the sequence of RNN. PointNet uses the operation of taking the maximum value as a symmetric function to approximate the function defined by any point set. The input order of the point cloud can be any sort of arrangement order, and there are a variety of arrangements. By using the maximum symmetric function, a 1024 dimensional vector will be generated in the model, and this result is the global feature that can best represent these points. Then the general convolutional neural network is used to reduce the dimension to achieve the purpose of classification.

$$f(x_1, x_2, \ldots x_n) = \max\{p \times g(h(x_1), h(x_2), \ldots h(x_n))\} \tag{4}$$

If the Max function is used directly, too many features will be lost. Map each point and expand it to 1024 bits. After feature extraction, do the Max operation to get the global output. The amount of insulator three-dimensional reflection data is huge, and the input data is about 100000 to hundreds of thousands of points. The amount of calculation using global attention mechanism is huge, so the algorithm uses local attention mechanism. In order to make full use of the spatial coordinates of the point cloud and the relative relationship between points and adjacent points, the input point cloud information contains the characteristics and spatial location of each point [21]. Input the point eigenvector x_i and the spatial coordinate q_i to find the n nearby points, and the set X_i consists of the eigenvalues calculated for each point is:

$$\beta_i = \delta \sum_{x_i \in X} w \, Tq(\mu(x_i)) \tag{5}$$

In the formula, w represents the weight matrix, T represents the characteristic matrix, q is the mapping function, and $\mu(x_i)$ is the point by point characteristic change function.

In the process of using laser radar technology to obtain three-dimensional reflection data of insulators, due to the existence of measurement errors, some sparse outliers will be generated, and the formation of these outliers will also be affected by various factors. Therefore, the distribution of outliers is irregular, without specific positions and states. From the perspective of local density, outliers are likely to exist in isolation or form high-density clusters. In the subsequent point cloud classification process, these outliers will cause significant interference to the algorithm, affecting the accuracy of classification and leading to incorrect segmentation [22]. Therefore, this paper innovatively uses a penetration filter to remove points that are not within the given value range in three dimensions.

The idea of pass through filter is to judge whether each power tower insulator point cloud data is within the value range of the dimension through each dimension and the value range under the dimension. If not, it will be eliminated. The specific implementation steps of the pass through filter are as follows:

(1) Obtain the power tower insulator point cloud dataset as:

$$L = \{l_i, i = 1, 2, 3, \ldots n\} \tag{6}$$

In the formula, l_i represents the total set of power tower insulator point cloud data.

(2) Obtain the maximum value point and the minimum value point in the three dimensional directions respectively, and record them as: $x_{\min}, y_{\min}, z_{\min}, x_{\max}, y_{\max}, z_{\max}$;

(3) According to the extreme points of power tower insulator point cloud data, a three-dimensional range parallel to the coordinate axis can be constructed as follows:

$$S_i = [x_{\min}, x_{\max}] \times [y_{\min}, y_{\max}] \times [z_{\min}, z_{\max}] \tag{7}$$

The spatial distribution of point cloud data for power tower insulators is discrete. The distribution of insulator point cloud data points in the main power tower is relatively concentrated, with high density and small distances between points and their neighborhoods; Outliers are sparse, far away from the main point cloud or scattered around the main point cloud, with a large distance from neighboring points, which can easily interfere with the fine-grained segmentation judgment. Therefore, this paper innovatively uses statistical filtering algorithms on the basis of penetration filters to remove outlier sparse outliers. The statistical filter method can be interpreted as calculating the average distance between all points in the point cloud and their nearest neighborhood points, assuming that all the average values conform to the Gaussian distribution, calculating their standard deviation according to the Gaussian formula, and setting a distance threshold. When the average distance calculated from a point in the power tower insulator point cloud data is greater than this threshold, the point is determined as an outlier and eliminated. The specific implementation steps are as follows:

(1) The power tower point cloud data collected by UAV equipped with LiDAR technology mainly includes ground points and non ground points, while non ground points include tower points, power line points, vegetation points and some low building points. The point cloud data set is obtained by processing through the pass through filter:

$$R = \{r_i, i = 1, 2, 3, \ldots n\} \tag{8}$$

(2) Most of the transmission line areas adopt high-voltage transmission. Therefore, in order to ensure the safety of the transmission line and residents, most of the construction sites of the transmission line are set up in the open no man's land. There are fewer buildings in this area, and most of them are low buildings, while there are more ground vegetation. It is found that there is a certain connectivity in the point cloud image. For any point, calculate the average distance between the point and the nearest k point, and record it as A_i;

(3) Since all average distances A_i obey Gaussian distribution, the average value μ and standard deviation σ of A_i can be calculated by the following formula:

$$\mu = \frac{\sum_{i=1}^{n} A_i}{n} \tag{9}$$

$$\sigma = \frac{\sum_{i=1}^{n} (A_i - \mu)^2}{n} \tag{10}$$

(4) Set the distance threshold to d, that is, the points in the point cloud that can be considered as outliers are all points that are outside the range of their neighborhood distance. The scale coefficient t is a constant, and its size is determined by the number of domain points;

(5) Traverse all power tower insulator point cloud data, eliminate all $A_i > d$ points, and observe the denoising effect.

Since the points on the ground account for a large proportion in the data set of power towers, it is considered to delete them in the preprocessing of point cloud information, so as to focus on better research of tower insulator information and improve the efficiency and accuracy of post-processing data [23].

Considering that the terrain of the collected area is relatively flat and there are many ground points, this paper selects a point cloud filtering method based on terrain filtering, namely cloth simulation filtering (CSF) algorithm, which can effectively eliminate ground points [24].

Cloth filtering algorithm is a physical simulation method. Generally speaking, it is assumed that a virtual cloth can fall down and fit the ground well according to its softness under the action of gravity. At this time, the shape of the cloth is called digital surface model (DSM).

The essence of cloth is a grid composed of various related nodes, also known as the particle model. There are interactive physical forces between each node to maintain elasticity. When the cloth is stressed, the corresponding nodes will show a certain displacement change under the action of the force, and the displacement is linearly related to the size of the force. Therefore, in the process of physical simulation of this algorithm, it is necessary to calculate the corresponding position of the cloth node on the basis of three-dimensional space. According to the projection direction of power tower insulator point cloud, the distribution node and point cloud are projected on the same horizontal plane, and the corresponding point cloud of each distribution node is found. Get the elevation value of each cloth node and its corresponding point cloud, and judge whether the point needs to be moved by the value. If the elevation value of a cloth node is less than or equal to its corresponding point cloud elevation value, move the cloth node to the location of its corresponding point cloud and mark it as a fixed point. The distance estimation algorithm is used to calculate the distance between the cloth node and the point cloud, and a threshold is set. If the distance is less than the threshold, the point cloud is divided into ground points, otherwise it will be divided into non ground points.

II. C.Fine optimization segmentation model of point cloud based on LSTM

Due to the non-linear characteristics of point cloud classification data for power tower insulators, conventional machine learning algorithms rely on the amount of training data for non-linear feature data segmentation. When the amount of historical data is insufficient, the segmentation error is large. Therefore, this paper innovatively introduces the LSTM algorithm with strong nonlinear learning ability to achieve fine optimization segmentation of the point cloud of power tower insulators. LSTM networks can remember information for a long time and can be easily called [25], [26]. During the training process, the long-term memory function of the LSTM network eliminates its dependence on historical training data and solves the problem of gradient vanishing in conventional machine learning algorithms, preventing information decay.

The LSTM based point cloud fine optimization segmentation model designed in this paper adds a unit state to the hidden layer of a conventional RNN network, transferring stored information from the sequence end of the RNN to the end of the RNN, thereby achieving long-term preservation of the state. The control of long-term state is achieved through three different "gate" structures, which control the modification of storage units at each step and determine how much of the previous unit state is retained at the current time, how much network input is saved to the unit state at the current time, and how much information continues to be transmitted downwards. Therefore, when data f_t is input i_t at each point o_t, the internal state can be continuously updated to output valuable information at any time [27]. By adding three gates to determine whether to save existing information, removing invalid information, and transmitting important information from early data over long distances [28].

The process of fine optimization segmentation function of power tower insulator point cloud is as follows:

Step 1: determine the forgetting gate of important information memory of power tower insulator point cloud data. Forgetting gate is to select important information from the historical information of the cell state for memory, and selectively discard the historical information in the cell state [29]. At this time, the input is the hidden layer information h_{t-1} at time $t-1$ and the input information x_t at time t. The calculation formula is as follows:

$$i_t = \lambda(f_t w_i[h_{t-1}, x_t] + b_i) \tag{11}$$

$$c_t = \tanh(i_t w_i[h_{t-1}, x_t] + b_c) \tag{12}$$

where, b_i is the data state of the candidate point cloud to be segmented at the current time, w_i is the hidden layer information, h_{t-1} is the hidden layer information at time t-1, b_c is the offset of the forgetting gate, $\tanh$ is the tangent function, and λ is the weight of the output gate.

In the process of updating the power tower insulator point cloud segmentation data, the output gate is divided into two parts. The new output information o is obtained by calculating the cell unit state. Then the output information o_i at time t and the cell unit state c_t at time t are calculated to obtain the hidden layer information e at time t through . the calculation formula is:

$$o_i = \varphi(c_t)\sum \tanh \int e \tag{13}$$

where, φ is the forgetting gate corresponding to time t; i is the input gate corresponding to time t; c is the cell unit state corresponding to time t.

Step 2: fine grained calculation of power tower insulator point cloud data segmentation. In the optimal segmentation, it is necessary to input new information into the unit state, and calculate the fine-grained segmentation of power tower insulator point cloud data. In order to improve the fine-grained segmentation of power tower insulator point cloud data in the transmission gate, the current fine-grained k_{t-1} of power tower insulator point cloud data is updated to k_t, the old state is multiplied with the current fine-grained, and some unnecessary information is removed to further refine the fine-grained segmentation of power tower insulator point cloud data as follows:

$$k_t = c_t * o_i k_{t-1} \sum v_t c_t \tag{14}$$

where v_t is the output of the forgetting gate.

Step 3: decide to output the segmentation result, which needs to be filtered. Determine the output content of the power tower insulator point cloud data segmentation result, and then pass it through a layer $\tanh$, and multiply the output result of layer $\tanh$ by the weight of sigmoid layer output to obtain the segmentation function, namely:

$$\theta_t = \sigma(w_i)[h_{t-1}, x_t] \int k_t v_t \sum_{t \in i} b_j \varpi_t \tag{15}$$

where, b_j is the output of the output gate; ϖ_t represents the segmentation ratio of power tower insulator point cloud data;

Step 4: fine segmentation function optimization of point cloud.

In the fine segmentation of power tower insulator point cloud, assuming that the model has just contacted the power tower insulator point cloud data in a certain period of time, it is necessary to input the relevant power tower insulator point cloud information into the unit state. In order to reduce the segmentation error of small insulator faults, a loss function is introduced to optimize the segmentation model, and the segmentation results are output as follows:

$$\theta_t' = \eta_i \sigma(w_i) / [h_{t-1}, x_t] sig(\beta) \int v_t \sum_{t \in i} b_j \varpi_t \tag{16}$$

In the formula, $sig(\beta)$ represents the loss function.

III. Example test and result analysis

The experimental environment is: the CPU is i7-9700K, the GPU is NVIDIA GeForce RTX 2080 Ti, the memory is 96 GB, and the deep learning framework is pytorch-1.7.0. Conduct experiments using Python language (version 3.8) and construct and train a fine optimization segmentation model for power tower insulator point cloud based on PointNet+LSTM using TensorFlow (version 2.6).

Point cloud segmentation of power tower insulators in a large mountainous wind farm. The power plant is distributed with a large number of power towers of different models and installation locations, and their insulators are exposed to complex natural environments for a long time, which may be affected by dust, bird droppings, rainwater erosion, etc., resulting in more complex point cloud data characteristics. At the same time, the mountainous terrain has significant undulations, which increases the difficulty of point cloud data collection and processing. Use high-precision Velodyne VLP-16 3D LiDAR equipment for point cloud data acquisition. This device has high measurement accuracy and scanning speed, and can accurately obtain three-dimensional point cloud data of power towers and their insulators under different lighting conditions. At the same time, it is equipped with a Global Positioning System (GPS) and an Inertial Measurement Unit (IMU) to record the status information of the collection equipment. Install the LiDAR equipment on the drone to scan the power towers in the power plant from multiple angles and heights. During the scanning process, the drone flies along the preset route to ensure that every power tower is fully covered. At the same time, record the timestamp, device location, and posture information for each scan. Use CloudCompare point cloud annotation software to manually annotate the collected point cloud data. During the experimental training, PointNet is used to classify the power tower insulator point cloud data, and 4096 power tower insulator point cloud data are randomly sampled as the training data. The laser point cloud data used in the experiment contains the desensitization data of 2284 base transmission towers. The data set was divided into 8:2 scale, with 1827 towers as the training set and 457 towers as the test set. In the large-scale scenic spot cloud segmentation task, the model batch size is set to 16, the learning rate is 0.001, the Adam optimizer is used, the loss function is the cross entropy loss, and the number of training rounds is 50. Different segmentation methods will get different segmentation results.

Indicator 1: precision optimization segmentation confidence of power tower insulator point cloud. This index directly reflects the precision of the model in segmenting the insulator point cloud of power tower. The larger the value, the better the segmentation accuracy and the better the performance of the algorithm.

Indicator 2: fine grained segmentation of power tower insulator point cloud data. The higher the value, the better the performance of the data before segmentation.

Indicator 3: average absolute error of fine optimization segmentation of power tower insulator point cloud. This value indirectly reflects the error in the processing of the segmentation model. The lower the value, the better the effect of model segmentation. The calculation formula of this value is:

$$RSEM = \frac{1}{n}\sqrt{\frac{r_i}{r_j}}\int r_i \tag{17}$$

In the formula, r_i represents the ideal average absolute error of fine optimization segmentation of power tower insulator point cloud, r_j represents the actual average absolute error of fine optimization segmentation of power tower insulator point cloud, and n represents the number of segmentation.

Indicator 4: point cloud segmentation results. Judge whether the global feature extraction and local feature aggregation effect can better capture the spatial structure and details of point cloud data, so as to achieve more accurate boundary recognition in the segmentation task.

Taking the methods of Reference [10] method and Reference [11] method as the comparison object and the randomly selected power tower insulator point cloud data as the research object, the confidence of the three methods for the optimal segmentation of power tower insulator point cloud is analyzed, and the results are shown in Table 2:

Table 2: Precision optimization segmentation confidence of power tower insulator point cloud

Amount of point cloud data/piece	Proposed method	Reference [10] method	Reference [11] method
500	99	96	92
1000	99	95	92
1500	99	94	91
2000	98	92	90
2500	98	90	90
3000	98	90	90

It can be seen from the data in Table 2 that with the change of the amount of power tower insulator point cloud data, the confidence of the proposed method, Reference [10] method and Reference [11] method optimization segmentation has changed to some extent. Among them, when the selected sample point cloud data is 1000, the confidence levels of the three methods are 99%, 95% and 92%, respectively, and when the selected sample point cloud data is 3000, the confidence levels of the three methods are 98%, 90% and 90%, respectively. It can be seen that the more the point cloud data segmented by the three methods, the lower the confidence level, but in general, the confidence level of the proposed method is higher than that of the other two models, indicating that the segmentation effect of the proposed method is better. This is because this paper aims at the irregularities and disorder of the original point cloud, and the method innovatively uses PointNet network to build the insulator positioning time stamp data classification network, which avoids the influence of the irregularities of the point cloud on the segmentation effect and improves the segmentation confidence.

Using the proposed method, Reference [10] method and Reference [11] method, and taking the randomly selected power tower insulator point cloud data as the research object, this paper analyzes the fine granularity of the data after optimized segmentation of power tower insulator point cloud by these three methods.

There are some differences in the fine-grained point cloud data after optimized segmentation by the proposed method, Reference [10] method and Reference [11] method. Among them, when the segmented sample point cloud data is 500, the fineness of the three methods after segmentation is 99%, 90% and 95%, respectively; when the segmented data is 2000, the fineness of the three methods after segmentation is 99%, 78% and 80%, respectively. It can be seen that the fine-grained effect of the proposed method after segmentation is better, which verifies the feasibility of the method. This is because the method of this paper innovatively uses the excellent long-term memory function and nonlinear learning ability of LSTM network to improve the data dependence of RNN network, and constantly updates the point cloud segmentation data of power tower insulator point cloud data during the training process, which improves the fine granularity of power tower insulator point cloud data segmentation.

The proposed method, Reference [10] method and Reference [11] method are used to analyze the average absolute error value of power tower insulator point cloud optimized by the three methods, taking the randomly selected power tower insulator point cloud data as the research object.

There is a large difference in the average absolute error value of the point cloud data after segmentation by the proposed method, Reference [10] method and Reference [11] method. From the height of the curve in the figure, the average absolute error of Reference [10] method and Reference [11] method are larger, indicating that there are more errors in the segmentation of these two methods. Compared with the proposed method, the average absolute error of segmentation is lower, less than 0.1%, indicating that this method is more feasible.

In combination with Reference [10] method and Reference [11] method, the insulator of the power line tower is divided.

The segmentation boundary of the tower insulator is clearer, and the clustering effect of the point cloud is better. It is completely consistent with the original image. This is because the pointnet network used in this paper preserves more details of the original data and retains more details of the original data. At the same time, the LSTM used in this paper has strong memory ability and can capture the long-term dependence in the sequence data, so that the model can comprehensively consider the image information of the tower insulator, directly process the unordered point cloud data, and retain the details of the original data.

In order to evaluate the efficiency of the algorithm proposed in this paper in processing point cloud data segmentation tasks of other insulators on power poles in different scenarios (such as sunny, rainy, and foggy days), the average running time was used as an indicator, and the proposed method and two advanced point cloud segmentation algorithms, PointNet++and RandLA Net, were compared. The results are shown in Table 3.

Table 3: Comparison results of average running time of different methods

Scene	Average running time/s		
	Proposed method	PointNet++algorithm	RandLA Net algorithm
Sunny days	22.3	35.6	31.2
Rainy days	25.1	42.1	37.4
Foggy days	28.2	48.8	43.6

From the perspective of average running time, as the scene changes from sunny to rainy to foggy, the running time of all three algorithms shows an upward trend. This is because in rainy and foggy environments, point cloud data is affected by factors such as rain and fog, leading to increased noise and decreased quality of the data. This requires more computing resources and time for algorithms to process these complex data. However, regardless of the scenario, the average running time of the algorithm in this article is significantly lower than that of PointNet++and RandLA Net. This indicates that the PointNet+LSTM model has strong adaptability and robustness in handling the fine segmentation task of power tower insulator point clouds. Even in the face of larger foggy scenes and more noisy data, it can complete the segmentation task faster. This is because the PointNet network can effectively extract features from the input point cloud data coordinates, avoiding complex feature engineering and data preprocessing steps. LSTM networks utilize their memory and nonlinear learning capabilities to update and optimize point cloud data in a targeted manner when processing temporal information, thereby reducing unnecessary computational complexity. Although PointNet++performs well in the field of point cloud segmentation, it adopts multi-layer nested sampling and grouping operations, which increases the computational complexity and running time when processing large-scale point cloud data. RandLA Net mainly achieves point cloud segmentation through random sampling and local feature aggregation. Although random sampling can reduce computational complexity, multiple iterations are required to obtain good segmentation results when processing complex point cloud data of power tower insulators, thereby increasing operation time.

IV. Conclusion

In this paper, a fine optimization segmentation model of power tower insulator point cloud based on pointnet+LSTM is proposed. By analyzing the characteristics of power tower insulator point cloud data; The pointnet network is used to directly input the coordinates of point cloud data, extract the time stamp of power tower insulator, and the through filter and cloth filter algorithm are used to remove the three-dimensional reflection data of insulator which is not within the value range, which effectively improves the quality of point cloud data; Using the memory and nonlinear learning ability of LSTM network, the forgetting gate of important information memory of insulator 3D reflection data is determined, and the insulator 3D reflection data is updated, so as to improve the fine granularity of segmentation, and realize the efficient processing and accurate segmentation of power tower insulator point cloud data. This method can significantly improve the detection efficiency and accuracy of power tower insulators, and ensure the safe and stable operation of power system. In addition, this method can also be applied to the point cloud data processing of other complex scenes, which has a wide application prospect and important practical value. Although LSTM networks have improved the data dependency problem of RNNs, they may still face difficulties when dealing with very long sequences. In the point cloud data of power tower insulators, if the point cloud sequence is particularly long or there are complex spatial relationships, LSTM may not be able to effectively capture and utilize these relationships. In the future, research can be conducted on how to combine other neural network architectures, such as Transformers, to enhance LSTM's ability to capture complex spatial relationships. This can include using attention mechanisms to improve the performance of LSTM or developing new neural network architectures to process point cloud sequence data.

Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Author Contributions

CG: Conceptualization, Formal Analysis, Methodology, Project administration, Resources, Writing–original draft. YW: Supervision, Validation, Writing–review and editing. ZH: Data curation, Software, Visualization, Writing–review and editing. SZ: Data curation, Writing–review and editing. TL: Writing–review and editing. HL: Writing–review and editing.

Funding

This work was supported by the Science and TechnologyProject (Key technologies for intelligent processing and efficient loading of massive laser point cloud data, J2023113).

Acknowledgments

The author would like to thank the reviewers for their valuable comments on the manuscript, which helped improve the quality of the paper.

Data Availability Statement

The raw data supporting the conclusion of this paper will be made available by the authors, without undue reservation.

References

[1] Yang, L., Chen, Z., Hao, Y., Lin, X., Yu, L., Li, Y., et al. (2024). Experimental study on ice monitoring method for 10 kV transmission line with tangent tower in alpine landform. High Voltage 9. doi: 10.1049/hve2.12372

[2] Chopra, S., Qiu, F., and Shim, S. (2023). Parallel Power System Restoration. INFORMS J Comput 35. doi: 10.1287/IJOC.2022.1258.

[3] Ghasemi, S., Darwesh, A., and Moshtagh, J. (2023). Critical loads restoration of distribution networks after blackout by microgrids to improve network resiliency. Electrical Engineering 105. doi: 10.1007/s00202-023-01832-4

[4] Zhong, J., Wang, C., Xie, K., and Hu, B. (2023). Incorporating public feedback in service restoration for electric distribution networks. IET Generation, Transmission and Distribution 17. doi: 10.1049/gtd2.12872

[5] Gao, Q., Yuan, F., Wang, X., Nan, M., Cheng, K., Dai, J., et al. (2023). A new method for active distribution network island fault recovery and reconstruction considering distributed generation. doi: 10.1117/12.3004481

[6] Kayal, P., and Giri Basumatary, R. (2023). Fostering restoration and power delivery efficiency by distributed generators and line switches in electricity distribution network. Energy Sources, Part A: Recovery, Utilization and Environmental Effects 45. doi: 10.1080/15567036.2023.2211031

[7] Yu, R., Li, P., Shan, J., and Zhu, H. (2022). Structural state estimation of earthquake-damaged building structures by using UAV photogrammetry and point cloud segmentation. Measurement (Lond) 202. doi: 10.1016/j.measurement.2022.111858

[8] Tomaszewski, M., Gasz, R., & Osuchowski, J. (2023). Detection of power line insulators in digital images based on the transformed colour intensity profiles. Sensors,23, 3343. doi : 10.3390/s23063343.

[9] Luan, Z., Lai, Y., Xu, Z., Gao, Y., and Wang, Q. (2023). Federated Learning-Based Insulator Fault Detection for Data Privacy Preserving. Sensors 23. doi: 10.3390/s23125624.

[10] Wang, H., Yang, Q., Zhang, B., and Gao, D. (2024). Deep learning based insulator fault detection algorithm for power transmission lines. J Real Time Image Process 21, 115. doi: 10.1007/s11554-024-01495-9.

[11] Fang, G., An, X., Fang, Q., and Gao, S. (2024). Insulator Defect Detection Based on YOLOv5s-KE. Electronics (Basel) 13. doi: 10.3390/electronics13173483.

[12] Yu, Y., Shi, L., Ran, Z., Qiu, S., Ou, J., and Wu, S. (2023). Research on Power Line Extraction and Modeling Technology Based on Laser Point Cloud., in Journal of Physics: Conference Series. doi: 10.1088/1742-6596/2503/1/012044

[13] Chen, J., Fu, Z., Cheng, X., & Wang, F. (2023). An method for power lines insulator defect detection with attention feedback and double spatial pyramid. Electric Power Systems Research, 218. doi : 10.1016/ 2023.109175.

[14] Aziz, E., Aouabed, F., Abdellah, H., & Dineva, A. (2023). Case Study: Optimizing Grading Ring Design for High Voltage Polymeric Insulators in Power Transmission Systems for Enhanced Electric Field and Voltage Distribution by Using a Finite Element Method.Energies. doi : 10.3390/en16135235.

[15] Wu, Z., Wu, Y., Lin, G., and Cai, J. (2024). Reliability-Adaptive Consistency Regularization for Weakly-Supervised Point Cloud Segmentation. Int J Comput Vis 132. doi: 10.1007/s11263-023-01975-8.

[16] Zeng, N., Li, J., Zhang, Y., Gao, X., and Luo, L. (2023). Scattered Train Bolt Point Cloud Segmentation Based on Hierarchical Multi-Scale Feature Learning. Sensors 23. doi: 10.3390/s23042019.

[17] Zhang, Y., Sun, Y., Wu, L., Zhang, L., and Meng, B. (2023a). 3D Point Cloud Semantic Segmentation Based PAConv and SE_variant. Instrumentation 10. doi: 10.15878/j.cnki.instrumentation.2023.04.001

[18] Ahn, P., Yang, J., Yi, E., Lee, C., and Kim, J. (2022). Projection-Based Point Convolution for Efficient Point Cloud Segmentation. IEEE Access 10. doi: 10.1109/ACCESS.2022.3144449.

[19] Li, D., Luo, J., Zhang, J., Liu, G., and Guo, Q. (2024). RGB pixel information fusion segmentation of dense point cloud data for transmission and distribution 3D digital corridors. Applied Mathematics and Nonlinear Sciences 9. doi: doi:10.2478/amns-2024-2169.

[20] Grandio, J., Riveiro, B., Soilán, M., and Arias, P. (2022). Point cloud semantic segmentation of complex railway environments using deep learning. Autom Constr 141. doi: 10.1016/j.autcon.2022.104425.

[21] Chang, K., Ma, W., Xu, X., Qi, X., Xue, X., Xu, Z., et al. (2024). A Point Cloud Segmentation Method for Pigs from Complex Point Cloud Environments Based on the Improved PointNet++. Agriculture 14. doi: 10.3390/agriculture14050720.

[22] Kawamoto, T. (2022). Feature Hole Extraction using 3D Point Cloud Segmentation and its Application to Registration. Proceedings of JSPE Semestrial Meeting 2022S, 209–210. doi: 10.11522/pscjspe.2022S.0_209

[23] Ren, S., Xu, S., Yu, S., Li, C., Zhao, J., and Liu, S. (2021). Target Recognition of Live Working Robots for Distribution Networks using LIDAR Point Cloud., in Proceeding - 2021 China Automation Congress, CAC 2021. doi: 10.1109/CAC53003.2021.9727416

[24] Kern, N., Grebner, T., and Waldschmidt, C. (2022). PointNet+LSTM for Target List-Based Gesture Recognition with Incoherent Radar Networks. IEEE Trans Aerosp Electron Syst 58. doi: 10.1109/TAES.2022.3179248.

[25] Okut, H. (2021). “Deep Learning for Subtyping and Prediction of Diseases: Long-Short Term Memory,” in Deep Learning Applications. doi: 10.5772/intechopen.96180.

[26] Ferraz, H., Gonçalves, R., Moura, et al. (2024). Synthetic images datasets of clean and dirty string insulators used in high-voltage power lines. Journal of the Brazilian Society of Mechanical Sciences and Engineering, 46 , 636. doi : 10.1007/s40430-024-05204-2.

[27] Yuan, X., Li, L., Shardt, Y. A. W., Wang, Y., and Yang, C. (2021). Deep Learning with Spatiotemporal Attention-Based LSTM for Industrial Soft Sensor Model Development. IEEE Transactions on Industrial Electronics 68. doi: 10.1109/TIE.2020.2984443.

[28] Zhang, Z., Qin, B., Gao, X., and Ding, T. (2023b). CNN-LSTM based power grid voltage stability emergency control coordination strategy. IET Generation, Transmission and Distribution 17. doi: 10.1049/gtd2.12890.

[29] Chiam, D. H., Lim, K. H., and Law, K. H. (2023). LSTM power quality disturbance classification with wavelets and attention mechanism. Electrical Engineering 105. doi: 10.1007/s00202-022-01667-5