Power distribution equipment and defect identification technology based on deep learning

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Abstract—In order to realize the collection of coordinate position of line pole and tower, and realize the field data collection of distribution equipment UAV and real-time recognition of front-end image, a calculation method of front-end edge of distribution equipment based on front-end RFID and depth identification was proposed. Firstly, the RFID identification instruction is sent to the front-end equipment for scanning through the interface provided by the RFID equipment, so as to obtain the physical ID number of the tower. Then, the edge computing equipment is used to carry out the equipment identification on the photos, so as to obtain the key equipment on the column. Fine photos were taken of the distribution network poles and towers to obtain the fine photo result data. Through the coordinate of the poles and towers, the photo coordinate associated with the equipment on the column and the collection coordinate of the physical ID, the trinity correlation was carried out to complete the AUTOMATIC GIS modelling of the distribution line and realize the geographical map display of the distribution line. This method can effectively identify the coordinate of power distribution line tower and equipment, and provide necessary data support for the modelling of power distribution line.

1. Introduction

With the continuous development of society, the demand for power is increasing, and the power grid system becomes huge and complex. The rapid growth of power components and transmission lines increases the difficulty and workload of maintenance and overhaul of the power grid system [1]. In order to ensure the stability of power supply and reduce economic losses, the line equipment should be carried out non-stop maintenance, replacement of parts and other live work. Image processing technology develops rapidly and is widely used in equipment identification and fault detection of power components [2]. By collecting the coordinate of the distribution line pole tower and the image of the equipment on the column, the equipment in the image is identified and the defect detection is carried out. It can provide necessary data support for the production of distribution network diagram.

Many scholars have made efforts to identify the line equipment and defects [3-5]. Yang [6] et al. proposed an insulator detection algorithm based on YOLO and realized the detection of complete insulators and missing insulators. Zhang Qian [7] et al. realized insulator recognition by using the LeNet_5 network structure of the feedback mechanism. Li [8] et al used deep convolutional neural network Alex Net [9] to extract features from images of power equipment, and then classified images of transformers, circuit breakers and other equipment through random forest model. Wei et al. [10]...
adopted deep learning target detection model SSD [11] to realize transformer identification and location on the basis of extracting deep features of substation images. In the aspect of defect identification, Yang et al. [12] took the Angle between adjacent aluminum wires as the feature quantity and used machine learning to identify wire scatter. Huang et al. [13] identified the broken and scattered strands of transmission wires based on the algorithm of radial basis probabilistic neural network. The defect samples of conductors studied by the above scholars are all from transmission lines, and the background between distribution lines and transmission lines is quite different. Therefore, more in-depth research is needed to apply the above methods to distribution lines. At the same time, because the characteristics of distribution network equipment and defects are different, the same method used to identify equipment and defects may lead to the reduction of identification accuracy.

Therefore, in view of the difference between distribution equipment and defect features, this paper adopts the improved SSD deep learning model to realize device identification, replaces VGG16 with ResNet50, increases the image size, and carries out feature fusion. The improved Faster-RCNN deep learning model was used to realize the identification of distribution network defects. VGG16 was replaced with Inception V2, and the image size was increased to obtain more accurate defect detection effect.

2. Front-end RFID Equipment

At present, the visible light camera carried by UAV is 123.7×112.6×127.1mm, as shown in Fig. 1. If the camera integrates RFID equipment, since the lens is in the front and the holder rotating device is on the top, the RFID equipment can only be integrated and installed at the bottom. Therefore, direct modification of the camera may have the following problems.

1) If the camera is integrated without changing the size of the camera, the small chip of the recognition equipment will lead to insufficient power and short effective recognition distance;
2) Modifying the shape of the camera may cause the camera to be too large and the stability of the PTZ and UAV to be reduced.

![Fig. 1 M210 UAV airborne visible light camera](image)

As the chip and antenna of the identification equipment need to ensure a certain size to have a good identification distance and effect, in order not to affect the stability and aesthetics of the aircraft and according to the current use of RFID identification equipment, RF-S7001 integrated reader module, as shown in Fig. 2, is not only small in size, but also has a high identification efficiency. Therefore, the RFID identification device is connected to the vacant cradle head of the aircraft for transformation.
Without modifying the camera, the RFID identification device can be seamlessly connected with the UAV through the integration method based on the extended PTZ load. The modified identification device is composed of DJI SkyPort and RF-S7001 integrated reader module, as shown in Fig. 3. The transformation scheme has the characteristics of low transformation cost, high degree of equipment integration, and good reuse rate, which effectively solves the problems existing in RFID identification equipment at the present stage.

DJI SkyPort is used to hook and fix the RFID device on the UAV, and the UAV will supply power to the PTP interface and the RFID device. The communication protocol and control and other transmission protocols of the Data transmission of DJI SkyPort are customized and developed through the Payload SDK. The communication and data transmission between integrated RFID equipment and UAV are realized. Device mounting entity view is shown in Fig. 4.
3. Image Recognition
Based on the front-end edge computing equipment, the image recognition algorithm is integrated to realize the UAV field data acquisition and real-time recognition of the front-end image, complete the automatic binding of the automatic identification equipment and line pole and tower coordinates, and provide basic data for the production of distribution network line diagram.

3.1. Introduction to the deep learning target algorithm
In deep learning target detection, the target detection model is structurally divided into single-stage detection model and multi-stage detection model. The single-stage detection model is fast, but the detection effect is poor for small targets. The speed of multi-stage target detection model is slow, but it has good detection effect for targets of all sizes.

3.2. Data set of transmission line of distribution network
The data set of overhead transmission line equipment and defects in distribution network has a total of 6268 images with a resolution of 1420×946. LabelImg software was used to annotate the collected data. There are five types of detection targets marked, including three types of equipment targets: transformer, fuse and switch; Two kinds of defect targets: missing pin and broken strand.

During data collection, the richness of the data set should be taken into account as far as possible, including illumination, background, shooting distance, shooting Angle, etc., as shown in Fig. 5.

A total of 19959 targets are marked in the data set, among which 6493 devices include switch switches, 2690 transformers and 6914 fuses. The defects include 116 broken strands and 3746 missing pins. The dimensions of the equipment and defect targets are shown in the figure. The target size of the equipment is relatively concentrated and large, with an average size of about 185×195. The target size of defects is scattered, and the overall size is small, the average size is about 51×48. In order to obtain a better detection effect, two models were used to detect the equipment and defects.
3.3. Detection method of distribution and transmission line equipment based on improved SSD
For distribution and transmission line equipment, SSD algorithm is adopted to realize equipment detection. The schematic diagram of SSD algorithm is shown in Fig. 6. The overall structure of SSD target detection is divided into three parts. The first part is the feature extraction network, the second part is the extra layer, and the third part is the classification and regression detection network. The SSD target detection algorithm takes VGG16 as the feature extraction network, and converts the full connection layer fc6 and fc7 of VGG16 into the convolution layer. In addition, additional layers were added to further extract the features extracted by VGG16. Finally, feature maps of six different scales were output in SSD model to realize multi-scale detection.
In the target detection algorithm, multi-scale feature maps are used to detect objects of different sizes to a certain extent, but the semantic information of low-level feature maps is insufficient, and the resolution of high-level feature maps is insufficient. In this paper, Feature Pyramid Networks (FPN) are used to solve the problem of insufficient processing of multi-scale changes in target detection. The structure of multi-scale feature map and feature pyramid network are shown in Fig. 7.

![Fig. 7 Different feature network structure (a) multi-scale feature map (b) Feature Pyramid Networks](image)

FPN still uses multi-scale feature maps for detection, but the difference is that the extracted multi-scale feature maps are not directly used for detection. In order to solve the problem of insufficient semantic information of low-level feature maps, the upper-level feature maps with rich semantic information are first sampled, and the upper-level feature maps with rich semantic information are added and fused with the corresponding low-level feature maps element by element to form a new low-level feature map, and then the detection is carried out. The FPN feature fusion process only includes simple 1x1 convolution and addition of each element, so the added computational amount is very small. However, because the low-level feature map integrates the high-level semantic information, the detection effect of small targets can be improved.

Meanwhile, in deep learning, the deeper the network depth of the model, the stronger the characteristic expression ability of the network. But the problem of gradient disappearance occurs in the training of deeper networks. Deep Residual Network (ResNet) presents a residual module. For a network block composed of an accumulated convolution layer, assuming that the input feature is x, the final learned feature of the network block is denoting F(x). In the use of residual network, the learning target is no longer H(x), but the learning residual F(x)=H(x)-x. The reason for this is that the learning of residual is easier than the direct learning of original features. Even if the residual is 0 in the case of network redundancy, the network block only does identity mapping, at least the gradient will not disappear.

The structure of the residual network is shown in Fig. 8. An additional connection is added at the beginning and end of the convolution block, so that input X can reach the end of the convolution block. The convolution block in the residual network only needs to learn the residual on the basis of x.
In the collected pictures of distribution equipment, the size of equipment is evenly distributed, but there are obvious differences among different types of equipment. The average pixel size of switch is 156×174, transformer is 339×324 and fuse is 152×164.

According to the characteristics of image data of distribution equipment, this paper proposes an improved SSD target detection algorithm for distribution equipment detection. Based on the SSD target detection algorithm, the following improvements are made:

1) Increase the size of the training image. Raw SSDS scale the data image to 300×300 pixels for training and prediction. In the detection task of network distribution equipment, the equipment size is small due to the long shooting distance. To improve this situation, the training size of the image is set as 640×640, and the size of the feature map is increased to improve the failure rate of the remote small target.

2) Replace the model feature extraction network. The distribution network and transmission line are in a changeable environment. In order to strengthen the feature extraction capability of the model, the feature extraction network is changed from VGG16 to Resnet50 in the background of the collected images.

3) Use FPN for feature fusion of multi-scale feature maps. For the 6-layer multi-scale feature map output by SSD, from deep to shallow, the feature map was up sampled and fused with the previous feature map. The high-resolution feature maps of shallow layer are fused with rich semantic information of deep layer feature maps to enhance the detection effect of small targets.

The improved model structure is shown in Fig. 9.

Fig. 8 Residual network structure diagram

Fig. 9 Improved Faster-RCNN defect detection for distribution networks and transmission lines
3.4. Defect detection of distribution network transmission lines based on improved Faster-RCNN

In view of the defects in transmission lines of distribution network, the improved Faster-RCNN algorithm is used to detect the defects. The faster-RCNN is a single-stage target detection algorithm, which has a good detection effect on small-size targets, and has a Faster detection speed compared with other multi-stage target detection algorithms.

The faster-RCNN target detection algorithm mainly consists of four parts in structure. The first part is the feature extraction Network, the second part is the Region Proposal Network (RPN), the third part is the classification and regression detection Network. The faster-RCNN target detection algorithm uses VGG16 network as the feature extraction network to achieve feature extraction of input images. Then, the extracted feature map is input into the second part of the RPN network, and the target region that needs to be identified is calculated as the region of interest. ROI pooling is used to generate the ROI feature map for the region of interest on the feature map, and then classification and regression prediction are performed.

RPN network is a full convolutional network, which greatly improves the speed of ROI generation. The detailed structure of RPN network is shown in the figure above, which is divided into two branches. The first branch classifies the detection box through SoftMax and determines whether it is the target or the background. The second branch calculates the offset of the check box. Finally, by combining the probability of positive and negative cases with the offset of detection box, an accurate detection box containing the target is obtained.

After the accurate detection box containing the target is calculated by RPN, the position containing the target corresponding to the accurate detection box can be found on the feature map, that is, the region of interest. However, the size of the region of interest is not uniform, so it cannot be classified and regressed directly. To this end, it is necessary to input the region of interest into the ROI pooling to achieve the unification of the size, and then perform classification and regression.

Unlike other convolutional neural networks, which develop in the direction of deepening the depth of the network, Inception network widens the network. Features of different scales can be extracted simultaneously with convolutional kernels of different sizes in the width direction of the Inception network. Inception widens the network, uses convolution kernels of different sizes to extract features of different scales on different branches, and reduces the amount of computation by decomposing large scale convolution into multiple small-scale convolutions.

In the collected data of distribution network defects, the size of defects is small and the size distribution is scattered. In view of the characteristics of distribution network defect data, this paper proposes to continuously improve the Faster-RCNN distribution network defect detection algorithm. Based on the Faster-RCNN target detection algorithm, the following improvements are made:

1) Increase the size of the training picture. In the collected distribution network defect data, the size of the original image is 1420×946, but the average size of the missing pin defect is only 45×45 pixels. If the original image is reduced during training, the size of the defect will be further reduced, which makes it difficult for the network to effectively learn small targets. In this paper, based on the original image, the long side of the defect image is sampled to 1365 pixels or the short side is sampled to 800 pixels. Instead of the original Fathering-RCNN, the long side is 1000 pixels or the short side is 600 pixels to increase the size of the training image, so as to improve the detection accuracy of small target defects.

2) Replace the model feature extraction network. The size of defects varied greatly, and the distribution was dispersive. In this paper, feature extraction network is replaced with Inception V2 network to satisfy feature extraction of defects of different scales.

The improved model structure is shown in Fig. 10.
4. Result and Analysis

In the experiment, 6268 pictures of distribution network equipment and defects were collected as training samples. Data were divided into training test sets in a ratio of 7:3. In the detection task of network distribution equipment, 3259 images are used as the training set, and 1396 images are used as the test set, with the size of 640×640. In the distribution network defect detection task, 1129 pictures are used as the training set, 484 pictures are used as the test set, and the input picture size is 1200×800.

The deep learning framework used in the experiment is TensorFlow, and the GPU device used is GTX2080Ti.

During the training of network distribution equipment testing model, the batch size was set to 64, the learning rate was set to 0.04, and the training iteration was 25000 times.

During the training of the distribution network defect detection model, the batch size is set to 1 and the learning rate is set to 0.0002. The learning rate decreases by 0.1 at the iteration of 90000 and 120000 respectively, and the training iteration is 200000 in total.

In order to verify the effectiveness of the algorithm proposed in this paper, experiments were conducted on the detection model of distribution equipment and defect detection model respectively. The test results of distribution equipment are shown in Tab. 1, and the test results of some equipment are shown in Fig. 11. The defect detection results of fault are shown in Tab. 2, and some detection results are shown in Fig. 12.

**Tab. 1 Detection Results of Distribution Equipment**

| Feature extraction network | Increase image size | feature fusion | Precision | Recall |
|---------------------------|---------------------|----------------|-----------|--------|
| 1                         | VGG16               | No             | No        | 0.8061 | 0.7742 |
| 2                         | Resnet50            | No             | No        | 0.8179 | 0.7801 |
| 3                         | Resnet50            | Yes            | No        | 0.8633 | 0.8176 |
| 4                         | Resnet50            | Yes            | Yes       | 0.8790 | 0.8335 |

**Tab. 2 Detection Results of Defect**

| Feature extraction network | Increase image size | Precision | Recall |
|---------------------------|---------------------|-----------|--------|
| 1                         | VGG16               | No        | 0.7012 | 0.6808 |
| 2                         | Inceptionv2         | No        | 0.7327 | 0.7064 |
| 3                         | Inceptionv2         | Yes       | 0.8070 | 0.8137 |
As can be seen from Table 1, replacing the feature extraction network of the model improves the accuracy of the model by about 1.2%. For the detection of distribution network equipment under complex background, replacing VGG16 with ResNet50 enhances the feature extraction capability of the model. Increasing the size of the input image can significantly improve the accuracy of the model by about 4.5%. This is because there are many pictures taken at a distance in the collected distribution network images, resulting in a relatively small proportion of the target device pixels. Increasing the size of the input image can retain more target features. After the multi-scale feature image is fused with FPN, the accuracy of the model is also improved objectively. Through analysis, it is concluded that the improved accuracy is mainly from the remote shooting targets. Experiments show that FPN can improve the detection effect of small targets.

As can be seen from Table 2, the improved Faster-RCNN algorithm proposed in this paper can greatly improve the effect of distribution network defect detection. After replacing the feature extraction network of the model, the accuracy of the model is improved, but the improvement is not significant. This is because the difficulty of defect detection of the distribution network is that the defect target occupies less pixel value than the picture taken. Improving the feature extraction ability of the model does not fundamentally solve this problem. After increasing the image size, the defect target retains more features, and the model accuracy and recall rate are greatly improved.

5. Conclusion

In this paper, a method of distribution network equipment and fault identification based on edge calculation is proposed. The improved SSD network model was used to realize the detection of network distribution equipment, and ResNet50 was used to replace VGG16 to increase the image size, and feature fusion was carried out. The experimental results show that the accuracy of the proposed algorithm reaches 87.9% and the recall rate reaches 83.3%. The improved Faster-RCNN model is used to detect distribution network defects, and Inception V2 is used to replace VGG16, and the image size is increased. Experimental verification shows that the accuracy of the proposed algorithm reaches 80.7% and the recall rate reaches 81.3%.

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