Defect Identification Detection Research for Insulator of Transmission Lines Based on Deep Learning

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Abstract. Traditional method of insulator defect identification is manually operated, which has low efficiency and high cost. Therefore, an automatic method of insulator defect identification is proposed in this paper. Firstly, image segmentation was operated by classification method of Random Forest (RF) to realize the object recognition of the insulator. Then, the method of Convolutional Neural Network (CNN) was adopted to classify the normal and defect states of insulators, and finally, the location of self-explosion defect identification was realized by Faster Region-Convolutional Neural Network (Faster R-CNN). A large number of images of insulators taken by Unmanned Aerial Vehicle (UAV) were used as experimental data to verify the method. The results show that the method in this paper could efficiently identify the defects of insulators, and the recognition rate reached 89.0%. The results can provide some references for the research of insulator defect identification of transmission lines.

1. Introduction

Insulator is an important part of transmission lines, which has an effect on electrical isolation and mechanical support. The status of insulator affect the normal operation of transmission lines. Accurate recognition of insulator defect have a key role to play in ensuring the normal operation of transmission system. Traditional inspection of transmission lines rely on manual inspection by operation and maintenance personnel mainly. This way is inefficient and has a high rate of missing inspection, which is not suitable for the reality of large-scale lines in China. At present, aerial photo inspection technology is relatively mature. The UAV carries high-definition camera and infrared equipment, and realizes the transmission of power inspection image based on network technology. Shandong, Zhejiang, Fujian and other places in China have achieved relatively successful results [1-3].

The aerial image of UAV is complex, which contains lots of background information and involves image segmentation and image recognition technology. Domestic and foreign electric power research institutions have carried out a lot of research on this. In literature [4,5], classification can be realized by support vector machine (SVM) after insulator feature extraction. In reference [6], based on the
visible and infrared images, multi-object positioning is carried out, and the actual position of the target body is obtained by approximate affine transformation. Chan Vese (C-V) model which is a typical representative of active contour model has the advantages of anti-interference and continuous boundary curve. So it is very suitable for image segmentation of transmission equipment [7, 8]. With the development of artificial intelligence and ubiquitous Internet of things, Faster R-CNN model which has powerful feature extraction ability and better recognition accuracy and efficiency than traditional methods is especially suitable for image recognition of power equipment [9-11]. Based on the deep learning method, this paper proposes an insulator defect automatic identification method to screen the defect insulator of transmission lines.

2. Random Forest principle
RF is a set of classifiers composed of multiple decision trees. Because of its high inclusion of the original signal noise [12], its classification accuracy is relatively high. RF classifies the original data by N decision trees, and the final output is determined by voting statistics, as shown in Figure 1.

![Figure 1. Schematic diagram of RF model.](image)

2.1. RF Training
Hypothesis decision tree is trained by training subset $D = \{d_i=(X_i, y_i)\}$. For the eigenvector $X_i$, see formula (1) for the calculation of classification function:

$$\text{Split}(X, j, y) = \begin{cases} X \geq \gamma \\ \text{else} \end{cases}$$ (1)

$X_{i,j}$ is the J-dimension eigenvector of $X_i$, $\gamma$ is the threshold value. If the classification parameters are different, different decision trees will appear. The best parameter can be confirmed according to the minimum criterion of Gini index, see formula (2):

$$G(D) = \sum_{k=1}^{m} \sum_{k \neq k} p_k p_{k'} = 1 - \sum_{k=1}^{m} p_k^2$$ (2)

$m$ is the $m$ classification of training subset $D$, and $p_k$ is the probability of the $k$-th classification. If $D$ is divided into two subsets, the Gini coefficient can be further calculated:

$$G_{\text{split}}(D) = \frac{|D_l|}{|D|} G(D_l) + \frac{|D_r|}{|D|} G(D_r)$$ (3)

2.2. Feature Selection
The eigenvector $u_i$ of $X_i$ and the within-class scatter matrix of training subset $D$ are calculated as follows:

$$S_W^{(k)} = \sum_{i=1}^{m} S_i^{(k)}$$ (4)
\[ S_i^{(k)} = \sum (\chi_i^{(k)} - u_i^{(k)})^2 \]  

(5)  

\[ S_W^{(k)} \] is the total within-class scatter matrix and \( S_i^{(k)} \) is the within-class scatter matrix of i decision tree.  

The inter class scatter matrix is calculated as follows:

\[ S_B^{(k)} = \sum_{i=1}^{m} n_i \sum_{i=1}^{n} (u_i^{(k)} - u^{(k)})^2 \]  

(6)  

\( S_B^{(k)} \) is the total inter class scatter matrix, \( n_i \) is the total number of samples of i decision tree, and \( u^{(k)} \) is the eigenmean vector of the training subset D.  

Equation (7) represents the criteria [10] for the discrimination of feature subsets:

\[ f(k) = \frac{S_B^{(k)}}{S_W^{(k)}} \]  

(7)  

3. Deep Learning  

3.1. Pre-Training Model  

There are relatively few insulators with defects, therefore the method of transfer learning is adopted. Expanding the number of samples through relevant amendments and supplements. Alexnet pre-training model is a mature convolutional neural network method and its algorithm principle [13] is shown in Figure 2.  

The AlexNet pre-training model consists of 5-layer convolution layer and 3-layer full connection layer.  

Output characteristic graph of convolution layer is expressed by \( X_{i,o}^{l} \). The local feature map of this layer is extracted by convolution function. Equation (8) is the calculation process.

\[ X_{i,o}^{l} = f\left(\sum_{i \in m} X_{i,o}^{l-1} K_{i,o}^{l} + B^{l}\right) \]  

(8)  

\( l \) is the number of layers of the layer, \( m \) is the convolution filter corresponding to the neuron, \( B^{l} \) is the offset, \( K_{i,o}^{l} \) is the convolution kernel.  

**Figure 2.** Pre-trained model structure of AlexNet.
Equation (9) shows the calculation method of $X_{o}^{l2}$ of output characteristic graph of full connection layer.

$$X_{o}^{l2} = f \left( \sum_{j \in l-1} w_{j} X_{i}^{l-1} + b^{l} \right)$$

(9)

### 3.2. Faster R-CNN Principle

Faster R-CNN is different from Fast Region-Convolutional Neural Network (Fast R-CNN) in that it has one more Region Proposal Network (RPN) to generate candidate regions, which can run computing directly in Graphics Processing Unit (GPU), greatly speeding up the computing speed [14]. See Figure 3 for the flow chart.

Equation (10) shows the calculation process of multitask loss function of Faster R-CNN.

$$L\left(\left\{ p_{i}^{*}, t_{i}\right\} \right) = \frac{1}{N_{cls}} \sum_{i=1}^{N} L_{cls}\left(p_{i}^{*}, p_{i}\right) + \frac{1}{N_{reg}} \sum_{i=1}^{N} L_{reg}\left(t_{i}^{*}, t_{i}\right)$$

(10)

$p_i$ and $p_i^*$ represent the predictive and true value of the object bounding box, $t_i$ and $t_i^*$ represent the predictive and true value of the category, $N_{cls}$ and $N_{reg}$ represent the normalized value of the category and the regression item, $\lambda$ represent the balance weight, $L_{cls}$ and $L_{reg}$ represent the category and the regression loss.

### 4. Insulator Defect Identification

#### 4.1. Experiment Preparation

The image data comes from the image of transmission lines taken by the operation and inspection personnel of a power company in South China through UAV, mainly double row lines insulator. The number of samples is sufficient and the background is relatively rich, such as trees, vegetable fields, and towers, etc. According to the actual environment, the adaptability research of this method can be better developed. See Table 1 for the specific sample information.

| Image type  | Training set | Validation set | Test set | Total  |
|-------------|--------------|----------------|----------|--------|
| Normal image| 200          | 100            | 300      | 600    |
| Defect image| 50           | 25             | 25       | 100    |
| Total       | 250          | 125            | 325      | 700    |
4.2. Experimental Process
The experimental flow is shown in Figure 4. The whole research is divided into two processes: image recognition and defect recognition. Image recognition which is based on Random Forest and Convolutional Neural Network (RF + CNN) mainly completes the accurate recognition of insulator object body. Defect location implements the classification of insulator object body by convolution neural network and locates the position of self exploding defects by Faster R-CNN classifier. Finally evaluating the whole insulator defect recognition rate.

![Figure 4. Process of defect identification.](image)

4.3. Data Analysis
After the application of this method, the results of horizontal and vertical double row insulator string identification and defect identification are shown in Figure 5.

![Figure 5. Insulator identification and defect marking.](image)

| Table 2. Accuracy of Insulator identification and defect. |
|----------------------------------------------------------|
| Identification type | Total number of insulators | The number of detected | Accuracy/% |
|---------------------|-----------------------------|------------------------|------------|
| insulator           | 700                         | 680                    | 97.1       |
| defect              | 100                         | 91                     | 91.0       |

It can be seen from table 2 that the accuracy of insulator identification is 97.1%, which means that all insulators can be identified basically and accurately. The accuracy of defect identification is 91.0%, which means the accuracy is high. It shows that this method can be applied to the accurate identification of insulator defects.
4.3.1 Object Recognition
In order to test the effect of RF + CNN algorithm, this paper compares it with CNN method. See Figure 6 for the accuracy of the two methods in different characteristic latitudes.

![Figure 6. Accuracy of different identification methods.](image)

It can be seen from Figure 6 that the accuracy of RF + CNN method is higher because of its strong anti-interference ability. For example, similar color vegetables interfere with insulator identification in Figure 5. Feature subset class discrimination $f(k)$ is better considering the influence of $S_B^{(k)}$ and $S_W^{(k)}$.

4.3.2 Defect Identification
Both deep learning and image processing [15] can be used for insulator defect identification. See table 3 for the accuracy and efficiency of the two methods.

**Table 3.** Comparison of defect recognition performance for different methods.

| Detection method | Accuracy/% | Average time /s |
|------------------|------------|-----------------|
| Image processing | 89.7       | 1.6             |
| Deep learning    | 91.0       | 0.5             |

The image still has some noise after filtering because the image processing is easily affected by background interference. So the accuracy of deep learning is higher. Deep learning only takes a certain amount of time in the stage of data training which can be carried out on GPU and the later detection speed is very fast. So deep learning is more efficient than image processing.

5. Conclusion
In this paper, an automatic identification method of insulator defects is proposed. RF + CNN is used to identify the insulator. CNN + Faster R-CNN is used to identify the self-explosion of insulator defects, and it has been successfully applied to the field operation and maintenance of electric power. This method can effectively and accurately identify the defects of insulator, and the recognition rate is 91.0%. The research results can provide some reference for insulator defect identification of transmission lines.

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