Faster R-CNN Algorithm Based Relay Protection Platen State Identification Method

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Abstract. Currently, the check of the relay protection pressure plate’s throw-out status is mainly carried out manually, due to the extremely large number of decompression plates, manual methods can cause detection errors due to fatigue. This paper proposes the processing of relay protection pressure plate photographs by using image processing techniques, the Faster R-CNN image recognition algorithm uses the feature of generating detection frames directly using RPN to identify the platen throwback status of the processed platen images, greatly improving the speed and accuracy of the detection frame generation. The experimental results show that, the method proposed in this paper effectively solves the problem of errors arising from manual verification checks of platen throwbacks, reduced workload for substation staff, the platen recognition rate can be over 98% correct.

1. Introduction
Rapid growth in the size of the electricity grid, the workload of calibration of relay protection equipment has increased dramatically. At present, the following problems exist in the manual checking of the status of relay protection and automatic device pressure plates by substation operators: (1) The large number of pressure plates in the installation makes verification a heavy task; (2) Mechanical and repetitive verification work and lack of quality and efficiency assurance; (3) Hazards of human and machine ergonomics affecting the occupational health of employees.

Faster R-CNN generates detection frames directly using RPN, which makes the generation of detection frames faster than other network models, thus improving the efficiency of image recognition. This paper proposes a relay protection platen state identification method based on Fast R-CNN, taking images of pressure plate protection cabinets by using handheld terminals, and greyscale, binarise and Gaussian filter the image. Building Fast R-CNN networks, training the network with the processed platen images to obtain a platen throwback state recognition network model. Through the image recognition test of 46 relay protection pressure plate screen cabinets in the main control room of a 220kV substation, the experiment shows that, the platen recognition rate can be over 98% correct, effectively solving existing problems with platen checking, reducing staff tasks, increasing correct checking rates and safeguarding staff occupational health.[1-4]

2. Platen Image Pre-processing
In order to improve the accuracy of Fast R-CNN in recognizing the opening and closing status of the platen, image processing including greyscaling, binarization and filtering are performed on the captured images before the image recognition of the platen. This paper uses Gaussian filtering algorithm to filter the image of the pressure plate, the effect is shown in figure 1.
3. Faster R-CNN Algorithm

3.1. Introduction to Convolutional Neural Networks
Convolutional Neural Networks (CNN) are Feedforward Neural Networks (FNN) that contain convolutional computation and have a deep structure. The convolutional neural network structure
includes: input layer, convolutional layer, pooling layer, connection layer, and full output layer. One feature of the input image is extracted by different convolutional kernels to form a feature map with multiple neurons per feature map.

In order to preserve the rich image features, a convolutional layer is designed to contain multiple feature maps with different weights. The pooling layer does a downsampling operation on the output of the convolution layer to achieve reduced parameters and lower resolution so that it can obtain robustness in translation and deformation. The alternating distribution of convolutional and pooling layers results in a progressively larger number of feature maps with progressively lower resolution, a bipyramidal structure.

3.2. Principle of Faster R-CNN Algorithm
Faster R-CNN is a combination of Fast R-CNN and RPN (Region Proposal Networks). RPN provides a coarse search range and Fast R-CNN uses region proposals to detect targets, training the network with images with the same features to give it the ability to identify the features of the target to be detected. The Faster R-CNN schematic, shown in figure 2.

![Faster R-CNN algorithm schematic](image)

**Figure 2.** Faster R-CNN algorithm schematic

3.3. Conv Layers
The Faster R-CNN uses the residual network as the backbone network to extract the features of the input image. The feature map is shared by the RPN layer and the fully connected layer. In the residual network only the pooling layer is the size of the output is reduced by 0.5 times compared to the input.

3.4. Region Proposal Networks
The RPN layer is mainly used to generate regional recommendations and is the most important feature of Faster R-CNN. This layer computes the anchor points of the corrected candidate frames to obtain the exact recommendation domain. Unlike the classical detection frame generation method, its direct RPN method greatly improves the speed of detection frame generation.
3.5. ROI Pooling
The ROI Pooling layer collects the input feature map and proposal, combines the information to extract the proposal feature map, and sends it to the subsequent fully connected layer to determine the target category.

Proposal=[x1,y1,x2,y2] corresponds to the M*N scale, which is first mapped back to a feature map scale of size (M/16)*(N/16) using the spatial_scale parameter; after that, each proposal is divided into seven parts horizontally and vertically, and each part is max pooling. After processing, the output is 7*7 in size even for proposals of different sizes, enabling fixed length output.

3.6. Classification
This layer first classifies the features in the recommendation boxes using the feature recommendation algorithm. Then, the position offset of each recommendation box is calculated by the regression algorithm to obtain the exact position of the detection box.

4. Experimentation and Analysis

4.1. Faster R-CNN Training Principle
Faster R-CNN training methods include training with alternating optimization algorithms, approximate joint training, and joint training. In this paper, we use the joint training method, first read the pre-trained VGG_CNN_M model and start the iterative training, similar to the detection network, and still use the conv layers to extract the feature map. The loss used for the entire network is shown in Equation 2.

\[
L((p_i), (t_i)) = \frac{1}{N_{cls}} \sum_{i} L_{cls}(p_i, \hat{p}_i) + \lambda \frac{1}{N_{reg}} \sum_{i} p_i \cdot L_{reg}(t_i, \hat{t}_i)
\]

(1)

\(i\) denotes the anchors index, \(p_i\) denotes the foreground softmax predict probability, \(\hat{p}_i\) denotes the corresponding GT predict probability. When the \(i\) th anchor and GT's IOU>0.7, the anchor is considered foreground, \(\hat{p}_i = 1\), and if IOU<0.3, the anchor is considered background, \(\hat{p}_i = 0\); as for those anchors with 0.3 less than IOU<0.7, they are not involved in training, generally a picture takes 256 anchors, generally bg=1, fg=1. \(\hat{t}_i\) represents the predict bounding box, where the image description is written to represent the corresponding foreground anchors corresponding to the GT box.

4.2. Model Training
The model training environment for this paper is the TensorFlow 1.4 machine learning platform based on the Python 3.7 version of Anaconda installed on a Windows 10 system, using Python 3.7 as the programming language. The steps to prepare the model before training are as follows.

1. vgg extracts features to get conv5_3, relu5_3.
2. roi_pool5: ROIPooling using the original roi to get pool5.
3. Place pool5 on the back two layers of vgg fc6,fc7.
4. Formation of two fully connected layers, cls_score for 21 (20 species + 1 background) classification probabilities, bbox_pred, get 84 points (21 x 4 coordinate points).
5. Calculate loss, loss_bbox respectively.

4.3. Experimental Results and Analysis
A large number of sample images are selected and the recognition model is obtained by image preprocessing and sample training. The effect of using the identification model to identify the state of the relay protection platen is shown in Figure 7, where the green box indicates that the platen is in a closed state and the red indicates a closed state.

The experiments were carried out with 200, 400 and 600 platen images and the results are shown in Table 1.
Table 1. Press sheet check list.

| No. | Number of platens | Number of correct | Correctness rate  |
|-----|-------------------|------------------|------------------|
| 1   | 200               | 188              | 94.000%          |
| 2   | 400               | 392              | 98.000%          |
| 3   | 600               | 595              | 99.167%          |

The experimental results show that the accuracy of the Faster R-CNN algorithm for checking the platen state is guaranteed, and the correct rate of recognition is gradually improved with the increase of the number of samples. The classification and detection of feature maps at different scales can yield sufficient semantic and location information. Besides, there are some external factors for recognition errors: blurred pictures, light reflections, and wrong shooting angles. Such issues should be addressed at the point of capture by the site inspector, for example by adding a photo clarity determination function to the equipment to alert site personnel to retake the photo if it fails.

5. Conclusion

This paper investigates the use of Faster R-CNN convolutional neural network to achieve relay protection platen throwback status recognition and conducts image recognition experiments on 46 relay protection panel cabinets in the main control room of a 220kV substation, with the following conclusions.

(1) Faster R-CNN generates detection frames directly using RPN, which can greatly improve the generation speed of detection frames and improve the efficiency of image recognition, solving the problem of low efficiency of classical detection methods in generating detection frames.

(2) Reduces substation costs, reduces staff workload, improves efficiency and reduces the probability of misthrow and miss-throw events, enabling safe and stable operation of the power system.

(3) This method has the advantages of being simple to use and accurate, with a recognition accuracy rate of 94% or more.

(4) The approach proposed in this paper can be applied to a number of scenarios, especially mobile apps and embedded devices, and can greatly enhance staff productivity.

6. References

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