Research on a Small Target Object Detection Algorithm for Electric Transmission Lines Based on Convolutional Neural Network

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***Abstract*—The intelligent detection algorithm can not only improve the efficiency of small object detection of transmission lines, but also reduce the safety risks of staffs. In order to find an efficient small target detection method for transmission lines, a fast region convolution neural network (RCNN) algorithm is proposed, and its region of interest (ROI) is improved by pooling operation, so that the target candidate region can contain the surrounding image information. The simulation results show that compared with SVM and Fast RCNN, the improved Fast RCNN algorithm has better performance in identifying and locating small targets. When the threshold setting is the same, the overall recognition accuracy of the improved Fast RCNN algorithm is the highest, and the corresponding test efficiency is higher in the test time comparison. In addition, the average missed detection rate of the improved Fast RCNN algorithm is 11.29%, and the average false alarm rate is 15.16%, which is lower than the other two algorithms. Its excellent performance makes it have high practical value in small target detection of transmission lines.**

***Key words*—Convolutional neural network; Transmission line; Small target detection; ROI**

I. Introduction

THE improvement of people's living standards and economic development have led to the increasing demand for energy. As one of the important energy sources in daily life, electricity has been scaling up. Power energy is transmitted through the transmission network, which is usually high-voltage transmission, so the safe operation of the transmission network is crucial. Once the transmission network fails, it will cause economic losses in relevant areas, and may cause other disasters affecting the stable operation of other transmission areas [1]. It is necessary to conduct security detection on transmission lines at regular intervals in order to ensure transmission network security. Transmission lines are often distributed in high altitude or remote areas, so traditional manual detection methods have many shortcomings, even security risks [2]. The development of intelligent technology makes it more widely used in power transmission and detection. The emergence of intelligent detection technology not only saves human capital, but also improves the efficiency of detection. The intelligent detection technology collects the characteristic images of the transmission line, then applies the corresponding recognition algorithm to identify and detect the equipment on the transmission line, and judges whether there is a fault according to its relevant characteristics [3]. For the detection of transmission lines, many scholars have proposed different methods. For example, Guo et al. [4] detected transmission line equipment with an optimized AlexNet anomaly detection model. They found that this method was effective in enhancing the recognition rate of power equipment images. Fahim et al. [5] detected and classified faults in transmission lines using a new self concerned convolutional neural network (CNN) model. They found that the model could classify and detect faults in transmission lines accurately. Tao et al. [6] put forward a novel deep CNN cascade structure to locate and detect defects in insulators. Their experiments found that the method was effective for detecting defects in insulators. The above relevant references have all studied the anomaly detection of transmission line equipment. All three have used relatively intuitive image detection, selected CNN suitable for image detection, and made different adjustments. The experimental results of these studies have verified the effectiveness of their algorithms for small target detection, but the efficiency and accuracy of the algorithms need to be improved. In addition, Nurmanini S et al. applied RCNN algorithm to the detection of virus infection and proved that it has a high accuracy [7]. Hu Z et al. applied CNN algorithm to facial feature and speech feature recognition, and the results showed that it had good accuracy and robustness [8].

In this study, we propose a fast region RCNN , so that target candidate regions can make full use of context information features. Traditional ROI operations only compress qualified candidate regions of different sizes to a unified size, without fully considering the impact of information around the compressed candidate regions on candidate regions. Therefore, this study improves the ROI pool by centralizing the information around the candidate regions and splicing them together so that the candidate regions to be detected contain the surrounding information. Compared with traditional methods, the proposed method has certain advantages and application value.

II. Detection Algorithms for Small Targets on Electronic Transmission Lines

A. Fast Region-Convolutional Neural Network-Based Small Target Detection Algorithm

Fast RCNN is a practical application of CNN in target detection algorithm. Fast RCNN algorithm has a similar basic principle with the traditional target detection algorithm, which includes image feature extraction, generation and recognition of target candidate regions, and classification of

Manuscript received May 24, 2022; revised November 14, 2022.
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features in candidate regions, but the difference is the image feature extraction step [9]. The Fast RCNN algorithm proposed in the study uses CNN to extract features, uses the region recommendation network to generate candidate regions on the extracted feature map, classifies and identifies the candidate regions [10], maps the identified candidate regions to the original image, and outputs the target detection results. Its flow chart is shown in Fig. 1.

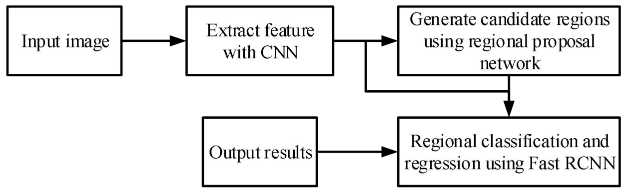


Fig. 1. Fast RCNN algorithm flow chart

① The original image is preprocessed by filtering, noise reduction and gray scale scaling.

② CNN is used to extract features from the image. Multiple convolutions and one pooling may also be used instead of one convolution and one pooling for practical applications.

③ After convolution and pooling, the feature map obtained from the last convolution operation is used as the input of the subsequent steps. In RPN, candidate regions are calculated according to the feature map obtained by the last convolution operation in CNN. RPN is a full convolution structure. In RPN, the input feature map is slide convolved, that is, each point on the feature image is regarded as an "anchor". Each "anchor" generates three candidate regions with different scales, and then generates three candidate regions with different aspect ratios for each scale. Three colors represent three different scales. Three frames of the same color are candidate regions, and they have different aspect ratios at the same scale. After each "anchor" generates a candidate area, convolution is used to check each anchor for convolution calculation, that is, score the candidate area, including the probability that the candidate area becomes a foreground area and a background area, as well as the coordinates when it becomes a foreground area. Candidate regions are arranged in descending order of foreground probability. Use the top candidate regions and their foreground region coordinates as the output of RPN [11].

④ The feature map obtained from the last convolution operation in step ② is combined with the output of RPN to perform the ROI pooling operation [12]. In this study, ROI is used to detect candidate regions of targets. ROI pooling then means pooling and compressing candidate regions. The specific steps are as follows: First, map the foreground part of the candidate region output by RPN to the feature map of the last convolution operation. Then, according to the target size of ROI pooling operation, the feature mapping in the foreground region is divided into multiple regions, and each region is pooled to the maximum. For example, the size of the foreground area with characteristic graph of 9×9 is compressed to 3×3, the feature map in the foreground area should be divided into 3×3, and then take each area of the maximum pool processing as the value of this area, finally we can get a scale of 3×3.

⑤ The features of the foreground part in the candidate region are imported to the fully connected layer. The classification score is calculated in the foreground area. Then the coordinates are calculated when the foreground area returns to the original image. Finally, judge the target type in the foreground box according to the classification score of the foreground box, and mark the target position according to the returned coordinates of the foreground box [13].

B. Improvements to the Small Target Detection Algorithm

ROI pooling operation compresses feature maps in candidate regions with different sizes into feature maps with the same specification. Finally, target detection algorithm uses ROI pooled feature map for target recognition and target area location. Therefore, the amount and accuracy of information contained in the feature map obtained through ROI pooling operation directly affect the detection performance of the entire detection algorithm [14]. After pooling ROI through the above fast RCNN algorithm, the algorithm identifies and locates candidate regions only by using the features in each candidate region, which ignores the feature association between different candidate regions.

Therefore, in order to improve the detection accuracy of fast RCNN algorithm for small targets, the ROI pool operation is improved. In addition to pooling the ROI of features in the candidate region, the regions with important context information near the candidate region are pooled [15]. After the selected candidate regions are pooled, they are combined with the ROI pool function of the candidate regions. The specific steps are as follows.

① The initial steps are the same as the above recognition algorithm. The convolution characteristic diagram is extracted by CNN. Then, candidate regions are generated on the last convolutional characteristic diagram and filtered. The number of filter candidate areas is set as N.

② Selecting a candidate frame n ($n \in N$). The center of n is a grid area of 3×3. The length and width of every grid are the same as n. The non-central grid is set as R_c ($c \in \{1,2,3,\cdots,8\}$).

③ Calculating the intersection-over-union (IOU) between the candidate regions except n and R_c. Other candidate regions' long edge is not longer than n, and their short edge is not shorter than one third of candidate region n, and their $IoU \geq 0.3$. Then, the set of the candidate context region of R_c is C_c, $c \in \{1,2,3,\cdots,8\}$.

④ Every candidate context region is scored by a 1×1 convolution kernel. The candidate context region with a highest score is taken as the significant context frame of R_c.

⑤ The features in candidate region n and the significant context region of R_c are both processed by ROI pooling. Then, the pooling features of candidate region n and the pooling features of the significant context region of R_c are jointed to obtain the ROI pooling features of candidate region n with significant context.

⑥ The ROI pooling features of candidate region n with significant context are imported to the fully connected layer. The classification score in the candidate region n and the coordinates of the candidate region when it is returned to the original image are calculated. Finally, the type of target in the frame is determined according to the classification score of candidate region n, and the target position is marked according to the return coordinates of candidate region n.

III. EXPERIMENT ANALYSIS

A. Experimental Data

① Two thousand images related to transmission lines are selected from X city power supply bureau in order to test how effective the fast RCNN detection algorithm proposed in this paper is. Small targets in the transmission line image include spacer, shockproof hammer, insulator, bird's nest, tower number plate, etc [16]. Before using the transmission line image for feature extraction and detection, the image is marked, that is, small targets in the transmission line image are marked with software annotation tools. The experimental parameter settings are shown in Table I.

TABLE I
THE SETTING PARAMETERS OF THE FAST RCNN ALGORITHM

Structure name	Settings
Convolutional layer	13
Pooling layer	5
Convolution kernel	64, size 5 × 5
Pooling frame	Size 2 × 2; move step length: 2
The size of the input image	1000 × 600

Table I shows the parameter settings of convolution network in Fast RCNN algorithm, including 13 convolution layers and 5 pooling layers. The size of the characteristic diagram after region of interest (ROI) pooling was 512 × 7 × 7. The pooled characteristic diagram was then input to two parallel fully-connected layers for class recognition and target frame localization, respectively.

The improved Fast RCNN algorithm had the same basic structure as described in the previous text, except that the significant contexts of the candidate regions were extracted using a 1 × 1 convolutional kernel before ROI pooling, as described in subsection 2.2 above. Each candidate region and the important context information around it were merged, and then used as the feature vector of the candidate region for subsequent recognition and target region location.

In order to further test the target detection performance of the improved algorithm, the research compared it with the previous Fast RCNN algorithm and the SVM based detection algorithm. In contrast experiments, directional gradient histogram was used as the recognition feature of SVM.

B. Evaluation Criteria

TABLE II
CONFUSION MATRIX

Type	Determined as a positive class by the algorithm	Determined as a negative class by the algorithm
Belonging to positive class actually	A	B
Belonging to negative class actually	C	D

The confusion matrix is used in the calculation of accuracy, recall and average accuracy [17], as shown in Table II, and its corresponding expression is shown in Formula (1).

$$\begin{cases} P = \dfrac{A}{A+C} \\ R = \dfrac{A}{A+B} \\ F = \dfrac{2PR}{P+R} \end{cases} \tag{1}$$

In Formula (1), P is the precision rate, R is the recall rate, and F is the average accuracy after the summation of precision and recall rate [18].

The calculation formula of the overlap degree of target frames is shown in Formula (2).

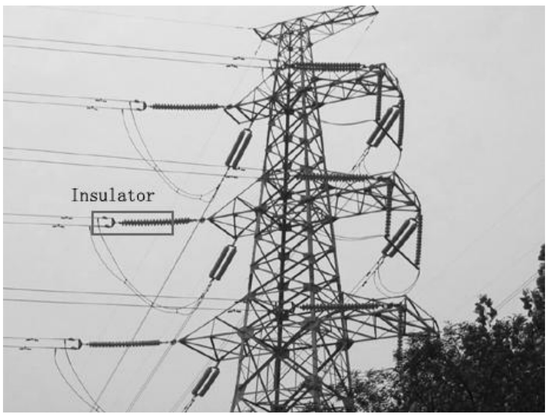
$$IOU = \frac{DR \cap GT}{DR \cup GT}, \tag{2}$$

where IOU is the overlap degree of target frames [19], DR represents the target frame predicted by the algorithm, and GT represents the actual target frame in the image.

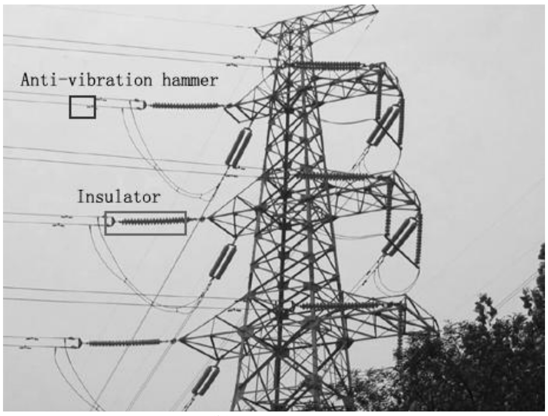
C. Experimental Results

Fig. 2 shows a representative of the transmission line image. To avoid multiple target boxes affecting the visualization, only one target box is displayed for each type of small target. Small target 2 in the figure includes a shockhammer and an insulator. SVM algorithm can only recognize larger insulators in small target detection results. The unimproved Fast RCNN algorithm identified the shockproof hammer and insulator in the small target detection results, but the target frame of the shockproof hammer obviously deviated from the location of the shockproof hammer. Because of its large size, the deflection of the insulator is relatively small. The improved Fast RCNN algorithm can not only correctly identify hammers and insulators, but also clearly label the position of small targets with boxes.

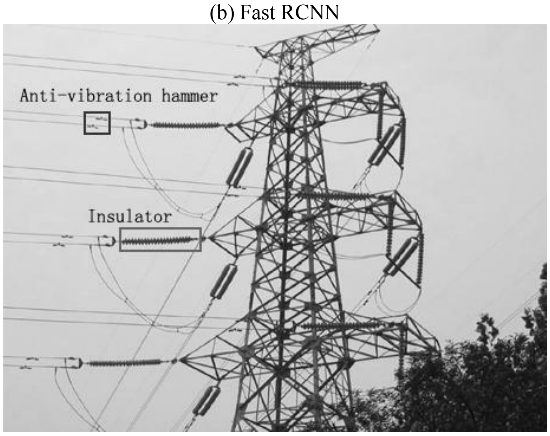
In this paper, when evaluating the accuracy of small target detection algorithm, the accuracy of target frame positioning is judged firstly according to the threshold value, and the target frames that meet the threshold value are counted only.



(a) SVM



(b) Fast RCNN



(c) Improved Fast RCNN

Fig. 2. Visualization detection results of three small target detection algorithms

Fig.3 shows the recognition accuracy of three small target detection algorithms when the threshold value of IOU is 0.5. The specific values of the recognition accuracy of the three small target detection algorithms for six kinds of small targets are as follows. The MAP of the SVM algorithm is 59.6%, 54.1%, 60.2%, 58.7%, 59.3% and 57.8% for spacer bar, anti-vibration hammer, insulator, bird nest, tower number plate and tower. The MAP of the Fast RCNN algorithm was 75.2%, 72.5%, 74.6%, 73.5%, 75.6% and 72.4% for spacer bar, anti-vibration hammer, insulator, bird nest, tower number plate and tower. And the MAP of the improved Fast RCNN algorithm was 89.2%, 85.3%, 88.9%, 86.5%, 88.4% and 87.9% for spacer bar, anti-vibration hammer, insulator, bird nest, tower number plate and tower. It can be seen from Fig. 3 that the SVM algorithm has the lowest recognition accuracy for small targets, the Fast RCNN algorithm has has a moderate recognition accuracy, and the improved Fast RCNN algorithm has the highest recognition accuracy for small targets.

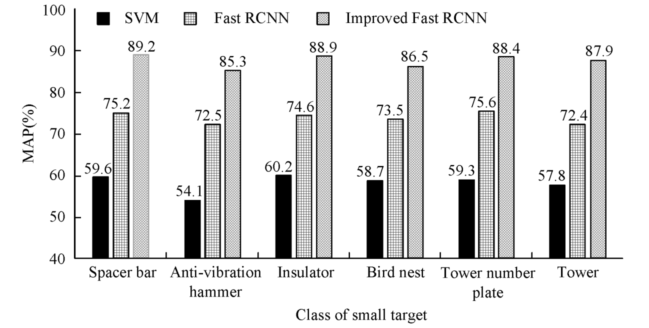


Fig. 3. Recognition accuracy of three algorithms when the threshold value of IOU is 0.5

Fig. 4 shows the overall recognition accuracy of the three small target detection algorithms when the IOU threshold is between 0.5 and 0.9. It can be seen intuitively from the figure that the overall recognition accuracy of the three small target detection algorithms decreases when the IOU threshold increases, that is, the three algorithms have the highest accuracy when the threshold is set as 0.5. For different thresholds, the overall recognition accuracy of the improved Fast RCNN algorithm is the highest, followed by Fast RCNN algorithm and SVM algorithm.

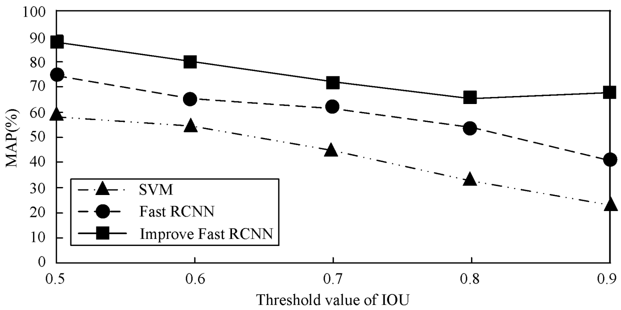


Fig. 4. Recognition accuracy of three small target detection algorithms under different threshold values of IOU

At the same time, the test time of the three algorithms is compared, which includes forward propagation and NMS time, excluding visualization time. The comparative results are demonstrated in Table III.

TABLE III
THE TEST TIME OF THE THREE ALGORITHMS IS COMPARED(MS)

Algorithm	mAP	FPS	Boxes	Input resolution
SVM	46.08	41	2000	300×300
Fast RCNN	62.94	9.3	300	1000×667
Improved Fast RCNN	65.47	7.9	1000	1000×800

It can be seen from Table III that although the SVM algorithm is the fastest, its resolution is low, so its detection effect is poor. Although the test time of the improved Fast RCNN algorithm is 2.53ms longer than that of the Fast RCNN algorithm, the number of target candidate frames generated by the former is significantly higher than that of the latter, so its efficiency and average accuracy are higher. In addition, the missed detection and false alarm rates of the three algorithms when detecting small targets are compared and analyzed, as displayed in Table IV.

TABLE IV
COMPARISON OF MISSED DETECTION RATE AND FALSE ALARM RATE WHEN THREE ALGORITHMS DETECT SMALL TARGETS

Undetected rate(%)					
Algorithm	Shockproof hammer	Tower number plate	Bird's Nest	Spacer	Average
SVM	26.31	32.15	44.84	26.45	32.44
Fast RCNN	18.63	13.54	16.21	15.97	16.09

Improved Fast RCNN	12.07	9.14	11.25	12.68	11.29
False alarm rate(%)					
SVM	35.01	32.98	37.61	30.17	33.94
Fast RCNN	22.67	21.84	25.34	24.31	23.54
Improved Fast RCNN	13.69	15.14	14.39	17.43	15.16

Table IV shows that the average miss rate of the improved Fast RCNN algorithm is 11.29%, which is 21.15% lower than that of the SVM algorithm, and 4.8% lower than that of the Fast RCNN algorithm. At the same time, the average false positive rate of the improved Fast RCNN algorithm is 15.16%, which is 18.78% lower than that of the SVM algorithm, and 8.38% lower than that of the Fast RCNN algorithm. Finally, to comprehensive test the overall performance of the improved Fast RCNN algorithm, its ROC curve is compared with that of Fast RCNN, as illustrated in Fig. 5.

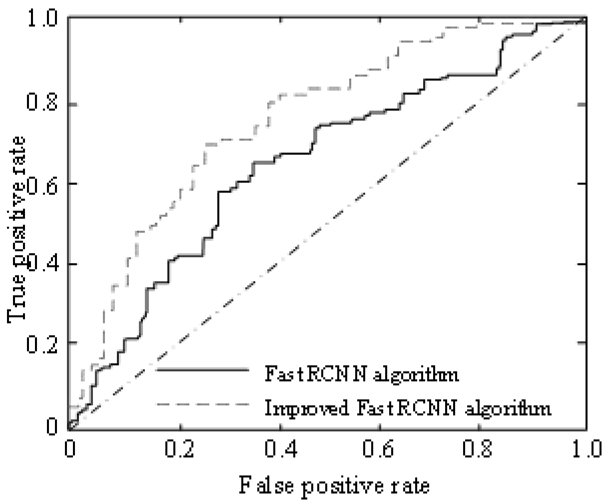


Fig. 5. ROC curves of the two algorithms

It is observed from the ROC curves of both algorithms that the curve of the improved algorithm is always above the Fast RCNN algorithm, so the proposed algorithm has a significantly larger area under the curve than the traditional algorithm. To sum up, the comprehensive analysis suggests that the improved Fast RCNN algorithm has the best performance.

IV. CONCLUSION

The detection of small objects in transmission circuits plays an important role in the secure and steady operation of of transmission lines. In order to achieve accurate detection, a Fast RCNN algorithm is proposed and improved. The experiment found that the improved Fast RCNN algorithm has higher detection accuracy on small target objects than the unimproved Fast RCNN algorithm and SVM algorithm. For example, when the threshold is set to 0.5, the overall recognition accuracy of the improved Fast RCNN algorithm is about 88.3%, 13.2% higher than that of the Fast RCNN algorithm, and 29.1% higher than that of the SVM algorithm. The test time comparison found that the improved Fast RCNN algorithm is the most efficient in testing. At the same time, the average false positive rate of the improved Fast RCNN algorithm is 11.29%, 21.15% lower than that of the SVM algorithm, and 4.8% lower than that of the Fast RCNN algorithm. The average false alarm rate is 15.16%, 18.78% lower than the SVM algorithm and 8.38% lower than the traditional one. In conclusion, the improved Fast RCNN algorithm can effectively detect small target objects on transmission lines, and has good detection performance. However, there are still shortcomings in the research, such as the imbalance of data sets corresponding to different small targets, which can be improved in future research.

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