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Airplane Detection in Remote Sensing Image Based on Deep Learning

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Abstract: Remote sensing image detection has always been a research hotspot, but due to the complexity and uncertainty of the background, the detection error rate is high. In the remote sensing images, due to the different size and number of airplanes, most of the algorithms have missed detection or error detection. In order to improve the detection efficiency, the Faster RCNN algorithm based on deep learning is proposed to detect the airplane of the remote sensing image. Firstly, the data set of the remote sensing images is established, and the training set, verification set and testing set are divided. Then, the Faster RCNN algorithm based on deep learning is proposed to detect airplane. Finally, the detection model can be obtained through training after combining the Faster RCNN with the remote sensing images. Experimental results show that the Faster RCNN has very high efficiency and excellent precision for airplane detection.

Keywords: Remote sensing image, Airplane detection, Deep learning, Faster RCNN, Image processing

1. Introduction

With the development of the remote sensing images, its application in both military and civilian fields has great value [1,2]. Especially in the case of higher and higher resolution, the development of the target detection based on the remote sensing image becomes more and more mature. Compared with other image collection methods, the remote sensing images have many advantages, such as wide range, large amount of information and high image resolution. The remote sensing images are used to detect airplane and other targets, which plays an important role in reconnaissance and detection. In this paper, airplane is taken as the target for the remote sensing image detection analysis.

The convolutional neural network (CNN) based on deep learning has the advantages of high accuracy and high speed, so it plays a great role in promoting the target detection. Traditional image detection technology has a lot of constraints, because the extraction from the image requires manual marking and other tedious process, it does not have the advantages of efficiency and speed. As an end-to-end detection architecture, the CNN performs representational learning of input information, recognizes and extracts similar features in space. Dong et al. proposed a target detection framework based on Mask-RCNN to detect the airplane [3]. According to the different dimensions of the airplane, a more reasonable set of the candidate frame scales is produced. Experiments show that the framework and the method combined had high detection accuracy. Xie et al. proposed an optimized YOLOv3 algorithm, which could greatly improve the error detection and missed detection in the process of small target detection [4]. The experiment shows that the algorithm has a higher detection rate, which increases the recall rate by 11.86 percent compared with the original YOLOv3 algorithm. Budak et al. proposed a deep CNN to detect targets in the remote sensing images [5]. An efficient CNN was constructed through the Normalization layer and the dropout layer, and it is experimentally verified that the architecture has a high accuracy rate of 95.21 percent. According to the remote sensing images of Google Maps, Chen et al. used a single neural network detection and limited training samples to achieve end-to-end airplane detection [6]. The experiment shows that the algorithm based on deep learning has important significance for the target detection. Xie et al. proposed a remote sensing image detection method based on deep learning, which improved the linear iterative clustering method [7]. Compared with traditional networks, the deep CNN model could not only detect clouds but also performed cloud classification. Experimental results show that this method has high detection accuracy and robustness. Vakalopoulou et al. proposed a high-resolution remote sensing image detection framework based on deep learning [8]. A very large training data is used to develop a supervised classification process. After experimental and quantitative verification, the developed method is very feasible.

In summary, significant progress has been achieved in the target detection based on remote sensing image, the real-time detection of target position in remote sensing image is very important for fast acquisition of monitoring information. Consequently, from the perspective of speed and accuracy, in order to further improving the detection speed of targets in the remote sensing images, it is very important to use the CNN based on deep learning to detect the target. Accordingly, the objective of this study is to adopt the Faster RCNN to detect the airplane in the remote sensing images.

The paper is organized as follows. In Section 2, the airplane remote sensing image data set is made. The analysis of the Faster RCNN algorithm is performed in Section 3. Section 4 carries on the remote sensing image airplane detection experiment. Finally, the paper is summarized in Section 5.

2. Acquisition and production of data set

In order to obtain enough remote sensing images of airplane, the Google map is used to collect data sets. In order to reflect the diversity of samples, different types of images are collected during the collection process of the data set, including different directions, different sizes and different numbers of the airplane. The collected image is uniformly named, the labelImg is used to mark the airplane in the image, and the location information of the airplane is obtained from the image to generate XML file. The airplane data set of the remote sensing images is divided, including 500 images in the training set, 100 images in the verification set, and 20 images in the test set.

The process of data set acquisition is shown in Figure 1. The data set is acquired on the Google map through screenshot, and the size of the image is saved as 400×400 pixels. The airplane images are captured in different scenes. The final result of data set collection is shown in Figure 2, including different states and different sizes of airplane. The information extraction method is shown in Figure 3. The left side of Figure 3 includes two marked airplanes, and the right side is the information of the XML file generated after marking. The main content of the information is the coordinate position of the airplane in the image.

Figure 1: Airplane screenshot

Figure 2: Airplane remote sensing image dataset

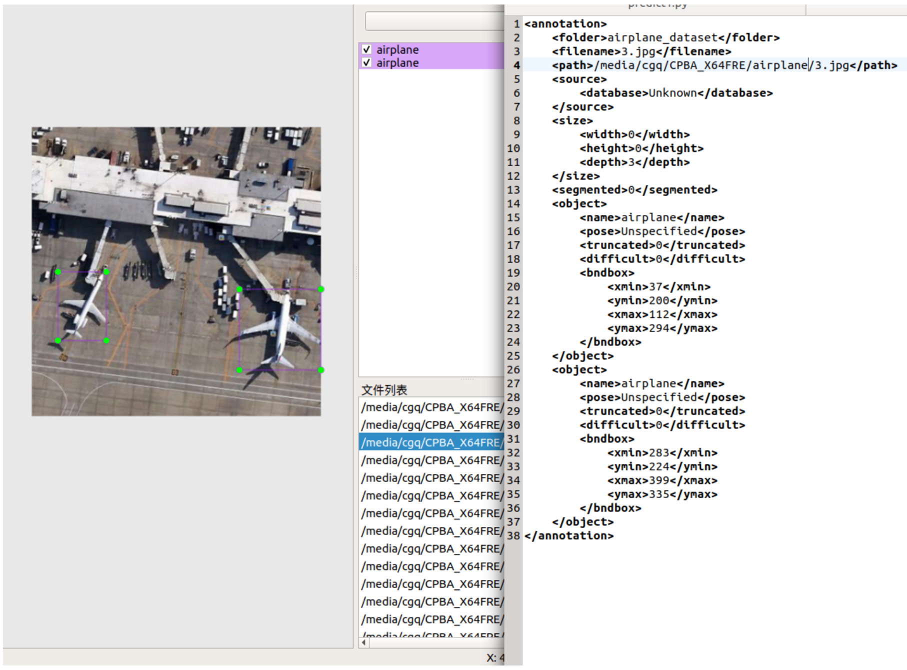

Figure 3: Airplane information extraction

3. Architecture of Faster CNN

The Faster RCNN is an optimized version established based on the Fast RCNN [9]. The Faster R-CNN can be divided into the following parts. The first part is the CNN composed of 13 conv layers, 13 ReLu layers and 4 pool layers. The function of this part is to extract the feature map. The second part is a full convolutional network (RPN) [10], which can extract region proposals through the region proposals network RPN. RPN can use GPU to calculate and improve efficiency, and can also greatly improve the speed and efficiency of detection by sharing the convolutional layer and detection network. The third part is the ROI pooling layer. The proposed feature map is generated by combining the region proposals extracted in the second part with the feature map generated in the first part. The fourth part is the classification layer. The feature map of the proposal is sent to the full connection layer. After three full connection layers, SoftMax classification function is used to calculate the category of each proposal, and RPN loss function is used to calculate the boundary box regression. More accurate boundary boxes are obtained. The architecture of the Faster RCNN is shown in Figure 4.

RPN is the core part of the Faster RCNN [11]. The detection process is divided into two links, one is the location, the other is the identification. In Figure 4, the feature map after the CNN is input to RPN, so RPN can be used for direct location. The Faster RCNN computes faster simply because RPN can choose a relatively lightweight network to accomplish location.

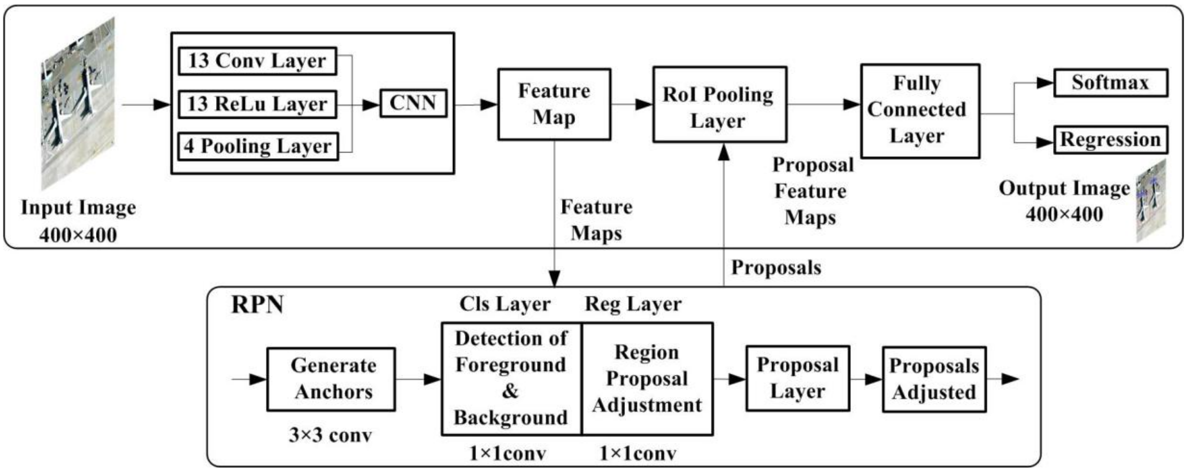

Figure 4: Architecture of Faster CNN

In RPN, the anchor is set on the entire feature map and Figure 5 shows the anchor generation mechanism. A 3×3 sliding window is convolved on the entire feature map, and k boxes are generated with each anchor as the center and k boxes are predicted to represent different region proposals. The size of the box has three ratios of 1, 0.5, and 2, and there are also three sizes of 128, 256, and 512. The classification layer in the upper left corner of Figure 5 indicates the probability of whether it is an object, and the border regression in the upper right corner indicates the four corrections from the region coordinate to the ground truth coordinate.

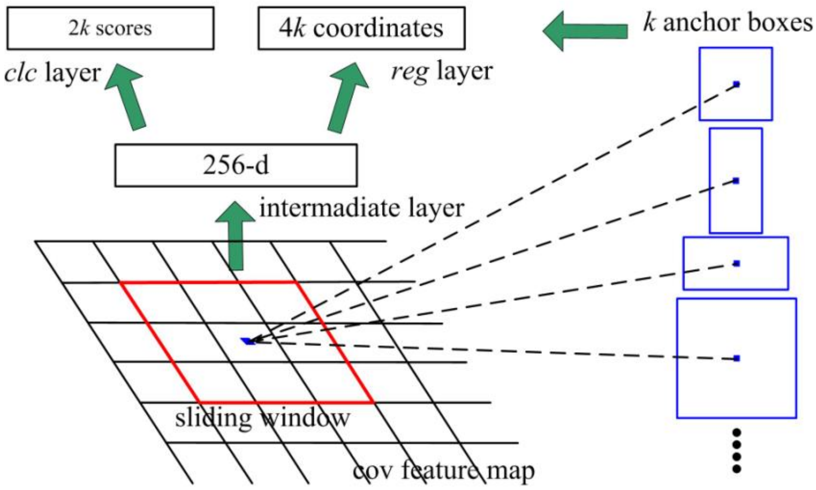

Figure 5: Anchor generation mechanism

4. Experiments

The experiments are implemented in the Caffe framework. The experimental hardware is configured with an Intel Core i7 processor and trained using the 8G NVIDIA GeForce GTX 2080Ti GPU. The operating system is Ubantu18.04 platform, and the programming environment is based on Python.

The number of iterations is set to 12000 in the training process, and the train loss curve is obtained after the Faster RCNN training, as shown in Figure 6. By observing the loss curve, the optimal convergence effect of the remote sensing image aircraft training is obtained.

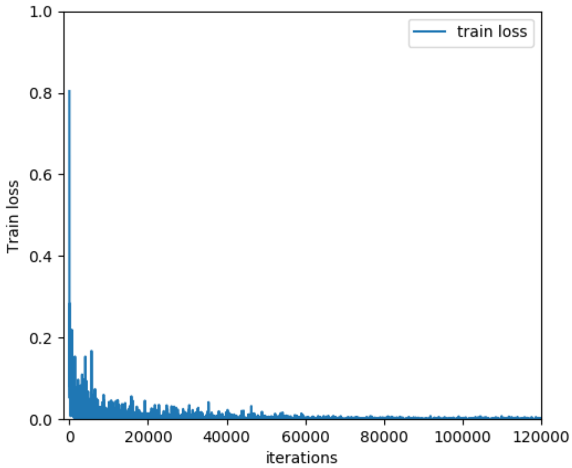

Figure 5: Anchor generation mechanism

The recognition results in Figure 6 are analyzed. All of the airplanes in the three images have been identified, including different directions, different sizes and different brightness. It can be concluded that the remote sensing image airplane detection based on the Faster RCNN has a very excellent effect.

Figure 6: Remote sensing image airplane detection results

The performance of the algorithm is evaluated by detecting accuracy and recall rate. The precision can be expressed as

$$Precision = \frac{TP}{TP+FP} \tag{1}$$

Where, TP is short for True Positive which means the number of positive samples that are correctly classified and FP is short for False Positive which means the number of negative samples marked as positive by error.

Recall rate can be expressed as

$$Recall = \frac{TP}{TP+FN} \tag{2}$$

Where, FN is short for False Negative which means the number of positive samples marked as negative by error.

The most commonly used evaluation standard is AP, which represents the area under the P-R curve, which is calculated by the precision and recall rate, and can be expressed as Equation (3). The Precision-Recall curve in this experiment is shown in Figure 7.

$$\text{AP} = \int_0^1 P(R)\,dR \tag{3}$$

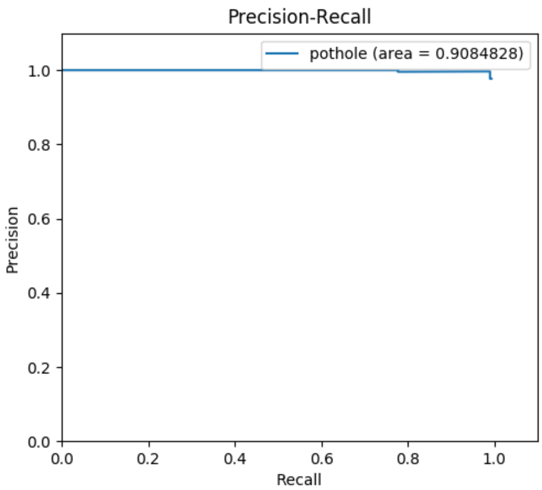

Figure 7: Airplane Precision-Recall curve

5. Conclusion

Based on remote sensing image, the Faster CNN is adopted in this paper to detect the airplane. Firstly, the data set is established based on the remote sensing images, the Google Map is adopted to collect the data set and the labelImg is used to extract the data set to obtain the airplane information in the figure. Then, the deep learning network Faster RCNN is introduced, the screenshots is input into the network and the airplane will be detected through trained. Finally, the analysis of experimental results shows that the network has high detection accuracy and speed. The application of the remote sensing image to airplane detection has laid a foundation and different kinds of target detection will be carried out in the future.

Reference

[1] Cheng G, Han J, Lu X. Remote sensing image scene classification: Benchmark and state of the art. Proceedings of the IEEE, 2017, 105(10): 1865-1883.

[2] Peng Ding,Ye Zhang,Wei-Jian Deng,Ping Jia,Arjan Kuijper. A light and faster regional convolutional neural network for object detection in optical remote sensing images. ISPRS Journal of Photogrammetry and Remote Sensing,2018,141.

[3] Dong YF, Zhang CT, Wang P, Feng Zhe. Airplane Detection of Optical Remote Sensing Images Based on Deep Learning. Laser & Optoelectronics Progress | Las Optoelect Prog, 2020,57(04):102-108.

[4] Xie M, Liu W, Yang MY, Chai Q, Ji L. Remote sensing image aircraft detection supported by deep convolutional neural network. Bulletin of Surveying and Mapping, 2019(06):19-23.

[5] Budak Ü, Şengür A, Halici U. Deep convolutional neural networks for airport detection in remote sensing images, 2018 26th Signal Processing and Communications Applications Conference (SIU). IEEE, 2018: 1-4.

[6] Chen Z, Zhang T, Ouyang C. End-to-end airplane detection using transfer learning in remote sensing images. Remote Sensing, 2018, 10(1): 139.

[7] Xie F, Shi M, Shi Z, et al. Multilevel cloud detection in remote sensing images based on deep learning. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 2017, 10(8): 3631-3640.

[8] Vakalopoulou M, Karantzalos K, Komodakis N, et al. Building detection in very high resolution multispectral data with deep learning features, 2015 IEEE International Geoscience and Remote Sensing Symposium (IGARSS). IEEE, 2015: 1873-1876.

[9] Li J,Liang X, Shen S M, et al. Scale-aware fast R-CNN for pedestrian detection. IEEE transactions on Multimedia, pp985-996,2017

[10] Simonyan K, Zisserman A. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556, 2014.

[11] Ren Y, Zhu C, Xiao S. Object detection based on Fast/Faster RCNN employing fully convolutional architectures. Mathematical Problems in Engineering, 2018.