Application of Target Detection Technology Based on Embedded Devices and Convolutional Neural Networks in Power Patrol

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Abstract. In order to ensure safe, stable and efficient operation of power production, regular inspections of power equipment and transmission lines must be carried out. With the update of power patrol technology, large volumes of inspection data increase manual workload, there is therefore an urgent need for intelligent inspection work. This study briefly describes the current state of research in target detection and power patrol, analyses the challenges of target detection technology in power inspections and explore possible solutions, finally take a look at its future development. It is hoped that this study will provide a useful reference for related research.

Keywords: Deep learning · Embedded devices · Convolutional neural networks · Target detection · Power patrol

1 Introduction

Currently, traditional target detection algorithms have difficulty meeting the requirements of the grid. Deep learning technology has the advantage of extracting features without manual design, which is highly suitable for the processing of diverse target features in power inspection. Therefore, this paper analyzes the application of target detection techniques based on deep learning and convolutional neural networks in power inspection.

2 Target Detection Technology Based on Deep Learning

In the field of power inspection, deep learning-based network models are mainly divided into two-stage models represented by the R-CNN series and one-stage models represented by the YOLO series and SSD.

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2.1 R-CNN

Convolutional neural networks have evolved from the original CNN, R-CNN, Fast R-CNN to Faster R-CNN. R-CNNs use a selective search algorithm to extract candidate regions, which requires a large amount of storage space due to the number of training steps and the time required. The emergence of Fast R-CNN, which adds border regression to replace SVM, solves the spatial overhead problem of R-CNN and improves the testing speed. However, Fast R-CNN still uses a selective search algorithm to extract candidate regions, which is slow and cannot be detected in real time.

Therefore, Faster R-CNN replaces the selective search algorithm with RPN when extracting candidate regions, enabling FasterR-CNN to complete candidate regions and feature extraction at the same time, realizing end-to-end training for target detection and significantly improving the detection speed of the network. As a result, Faster R-CNN is mostly used as the detection algorithm in practical power inspection scenarios.

2.2 YOLO

The advent of YOLO (YouOnlyLookOnce) has, to some extent, increased the efficiency of the two-stage target detection algorithm. Redmon unifies feature extraction, recognition and localization in a single convolutional network. This is how YOLOv1 was born. Using DarkNet-19 as the backbone, Redmon modified YOLOv2 [1] and designed YOLOv3 [2], using K-Means to extract the scale of anchor box to improve the detection accuracy and further improving the accuracy and recall of the model with the newly designed Darknet53. Bochkovskiy proposed YOLOv4 to improve the detection of small targets by borrowing the sampling method of FPN [3]. YOLOv5 algorithm acts as a representative of single-stage detection algorithms with high detection rate and accuracy. YOLO models are suitable for deployment on UAV-mounted embedded devices and are often used for real-time inspection.

2.3 SSD

The SSD algorithm combines high detection accuracy with high detection speed, featuring multi-scale to improve detection of small targets. Due to the presence of small sized targets such as anti-vibration hammers and bird nests in power inspections, they are mostly detected by improved SSD algorithms. For example, changing the backbone of SSD to a DSSD network with ResNet-101 to boost sensitivity to small targets.

3 Overview of Electrical Inspection

In recent years, new technologies such as drone inspections, robotic inspections and helicopter inspections have been gradually introduced to the power grid, using loaded inspection devices to inspect key objects of the transmission lines. Due to the low efficiency of robot inspection and the certain damage it will cause to the power lines by its own weight, this study mainly introduces helicopter inspection and drone inspection.

3.1 Helicopter Inspection

Helicopter inspection detects faults and defects from transmission lines by analysing and processing helicopter aerial image data, mostly used for high voltage transmission line inspections. In terms of transmission line extraction and identification, Tong Weiguo [4] used an improved Marr-Hildreth edge detection algorithm and morphological analysis to identify transmission lines; Li Zhengrong [5] used a neural network method to extract transmission lines after filtering out background noise. In the area of fault diagnosis, the Central China Power Grid Company exhibited "research on the application of airborne multi-angle multispectral imaging technology in power systems", using multi-angle image data to obtain the distance between conductors and surrounding objects, and completed an experimental prototype and flight experiments.

3.2 Drone Inspection

UAV inspection has the advantages of low cost, safety and efficiency, which are carried out on overhead lines by means of on-board sensing equipment. It is easy to find faults and defects, therefore can effectively reduce the cost of grid operation.

In terms of function, UAVs mainly play the role of remote sensing carrying platforms in power inspections. 1) Remote sensing is used to detect the operation of key electrical components. 2) Visible light remote sensing is used to examine changes in the characteristic properties of electrical equipment. 3) Infrared remote sensing uses infrared thermal cameras and other equipment to detect the thermal radiation of the target to determine the operation of the equipment, and is applicable to detect abnormal heat generation in substations, overhead lines, power stations and other equipment. 4) UV remote sensing for the detection of corona discharge and surface local flashover of electrical equipment. 5) LIDAR is mostly mounted on fixed-wing UAVs, mainly to be used for mapping the channel environment of overhead lines and 3D reconstruction.

Autonomous navigation is the core technology for achieving autonomous drone inspections. Autonomous navigation for power drone inspection can be divided into two stages: 1) Flight in the area between towers. Tan Min's team from Chinese Academy of Sciences [6] placed the UAV on the side area of the conductor to fly and designed TowerRCNN, a deep learning based tower detection network, to determine the UAV flight heading by combining VP and detection results. 2) The near-tower area is a key area for UAV inspection. There are a large number of electrical components in this area and the phenomenon of mutual occlusion is serious. In order to ensure the quality of inspection, Tan Min's team also proposed an improved ORB-SLAM framework [7] to solve the UAV positioning problem in the near-tower area.

4 Challenges and Solutions for Target Detection in Power Patrol

4.1 Dataset Issues

There is currently no publicly available dataset for electrical inspections on a global scale. The difficulty in building an inspection image dataset lies in the huge amount of annotation work. Another problem is that the quantity distribution of all kinds of defects in the inspection image is extremely unbalanced.

The problem of image dataset can be considered from the following aspects: 1) Develop standardised methods of power defect description and classification; 2) Develop evaluation standards of image processing and quality to enhance data availability and inspection lean; 3) Take into account inspection regional characteristics when establishing image dataset; 4) Build an image intelligent processing system to accelerate the development of artificial intelligence image processing technology and reduce the manual workload in inspection work.

For class imbalance problems, consider expanding the data with data enhancement techniques such as flipping, cropping, colour dithering, etc. Another possible option is to expand the dataset by image synthesis, for example by trying to train the model using only synthetic images or images of related tasks.

4.2 Detection Strategy Issues

In power inspection, the percentage of defective points of components in the original image is small, and most current CNN-based target detectors, such as YOLO and Faster-RCNN, are far less effective in small object detection than in large object detection [8].

One possible solution is to use a multi-level detection strategy. Significant targets are detected and segmented, and then use a more detailed defect detection model to detect them. However, the defect classification method in the multi-level detection suffers from the problem of accumulating errors step by step and is not fully appropriate for machine vision.

4.3 Detection Algorithm Issues

The training set can hardly cover all the defect patterns due to the cluttered scenes of power inspection images and the various forms of defects in the detection targets, which is also a huge challenge for deep learning-based defect detection.

One potential approach is migration learning, such as zero-time-learning [9], which allows the network to process classes that have never been seen before but have similar features by training on related tasks; or one-time learning [10], which uses a small amount of training data to retrain a model that has already been trained on the task; generative adversarial networks GANs can also be used to reduce the difficulty of data set collection.

4.4 Detection Limitations

In defect detection, there are still more than 30 types of defects that cannot be detected solely by visible light images. The fusion of multiple sources of data is a feasible solution. In terms of power inspection methods, there are infrared, ultraviolet and LIDAR in addition to visible light. Multi-source data fusion can effectively extend the scope of defect detection. The fusion methods include direct fusion of multiple sources of data, fusion of feature attributes extracted from the data and fusion of intermediate processing results. For example, stereo vision and LIDAR, monocular vision and inertial/magnetic sensors, etc. The complementary information about multi-source data fusion helps to improve the detection performance of deep learning models.

5 Conclusion

Regular power inspections are the basis for the long-term safety and stability of power systems. Deep learning, whose excellent abilities of image feature mining and generalization makes it promising to cover the real-time detection of power inspection, has great potential in this field. The author propose the following perspectives for the research of target detection in power inspection:

Deep learning requires the backup of big data, and it is crucial to build a more comprehensive database of power inspection images. In the future, small sample learning can be studied to solve the problem of lack of power data and time-consuming and labor-intensive labeling. Meanwhile, the richness of the collected sample set should be emphasized to enhance the generalization ability of the detection network.

In the future, the visible light data will be integrated with infrared/ultraviolet images, satellite remote sensing, laser scanning, inspection trails and other data to deepen the application of multi-system and multi-source information data fusion and promote the transformation of power inspection to collaborative three-dimensional multi-source intelligent inspection.

The application of deep learning technology in power patrol is in its initial stage, and future research on deep learning technology should be demand-oriented, combined with front-line production, so as to expand the application level with research progress and form a virtuous cycle with iterative progress.

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