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Research on computer vision application in industry field: focus on distribution network engineering

Fan Ke[1], Huang Chen-Yu[2], Liu Weijia[3], He Kun[4], Shi Bin[5], Wu Yanyou[3]

[1]*Arizona State University, Phoenix, United States*
[2]*Illinois State University, Chicago, United States*
[3]*Trine University, Phoenix, United States*
[4]*Illinois Institute of Technology, Chicago, United States*
[5]*University of Chinese Academy of Sciences, Chengdu, China*

Abstract. The operation of distribution networks is currently facing potential safety and quality defects that pose significant hazards. One solution to strengthen management, reduce manual workload, and improve efficiency and quality is by applying deep detection networks for dynamic defect detection in distribution network engineering. To start, defects in distribution network engineering are classified. Then, advanced deep detection networks and their applications in dynamic defect detection are researched and analyzed, along with a review of existing research. Key issues and their solutions for deep detection network application in dynamic defect detection in distribution network engineering are summarized. Finally, future research directions are explored to provide valuable references for future studies.

Keywords: deep learning, application of deep learning target detection, computer vision.

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INTRODUCTION

Application Status of Deep Detection Network in Distribution Network Defect Detection

Overview of the development trend of deep networks

In recent years, deep networks [1] have represented a significant breakthrough in the field of machine learning. However, compared to their success in application, the theoretical foundation of deep networks remains relatively weak. As networks continue to deepen, they face increasingly severe challenges, and addressing these problems is crucial to promoting the development of distribution network engineering [2]. The detailed research and application of defect detection technology plays an essential role in this promotion. Deep neural networks face several issues, such as non-convex loss functions, overparameterization, and poor generalization ability due to high degrees and over-parameters. Additionally, deep neural networks require substantial amounts of training data, and the computational cost of second-order optimization methods is high. To address non-convex optimization issues, researchers have proposed using gradient ascent on non-convex targets, stochastic super-complete tensor decomposition, and the Kac-Rice formula and random matrix theory to solve deep network minimum values. Similarly, the spectral algorithm can avoid complex non-convex optimization issues of convolutional neural networks under the framework of moment estimation [3].

To address the issue of deep network degradation, a paper proposed the deep ResNet, which introduced a residual unit based on the visual geometry group (VGG) network. This approach effectively addressed gradient disappearance and explosion problems. To mitigate overfitting in deep networks, several optimization schemes have been proposed, such as early truncation to stop iteration before the model overfits, sample expansion to increase the training set data and correct model parameters, regularization by introducing appropriate regularization items in the loss function, and Dropout operations to randomly inactivate sub-neurons [4], reducing the risk of overfitting and enhancing the model's generalization ability.

The application of deep detection network in target detection

Apart from the inherent challenges faced by the field of deep networks, the field of image recognition and target detection based on deep detection networks also confronts several issues that require addressing. These problems hinder the rapid development of dynamic defect detection technology in distribution network engineering, which includes multi-target detection and recognition in complex scenes, dynamic changes in the number of detection objects, increased complexity of sample labeling and modeling, unbalanced target sizes, low tracking efficiency for targets of different sizes, limited or scarce samples resulting in poor adaptability, insufficient model interpretability in specific scenarios [5], and difficulty in balancing network model complexity, real-time detection, and accuracy.

The performance of image classification and object detection can be significantly enhanced by improving the deep detection network. Several notable detectors have emerged in recent years that represent the evolution of target detection algorithm models [6]. For instance, Faster R-CNN, proposed in literature, uses neural networks to generate candidate detection frame generation networks and achieves end-to-end training, significantly improving the training speed for object detection. YOLO and its derivative series follow the basic idea of dividing the image into multiple regions to predict the bounding box and probability of each region, improving the detection speed. Similarly, the multi-target detection algorithm, represented by SSD and its derivative series, directly predicts the target category and bounding box to improve detection speed. RetinaNet introduces a focal loss function and reconstructs the standard cross-entropy loss to optimize target detection performance in complex scenes. Most detectors optimize network structure using technical means such as weighted residual connections, cross-stage partial connections, and improved CloU loss functions to improve detection performance.

RESULTS

Application of deep detection network in target detection of distribution network engineering

As the deep detection network model continues to iterate in the machine vision field, the accuracy and real-time performance of target detection in the distribution network engineering field have improved. Current research focuses on the application of various mainstream target detection algorithms to this field, with continuous optimization and improvement [7]. This section will classify the status quo of safety and quality defects in distribution network engineering based on text, personnel, and equipment, from the perspective of target detection types.

Text detection

The detection of text involves various aspects, including identifying whether the photo of distribution network equipment contains a nameplate or logo, and determining if the nameplate has been removed. It also entails recognizing the specific content of the nameplate and logo of the equipment, and detecting any image fault defect text in distribution network equipment, to quickly identify whether there are defects. Text detection and recognition are part of target detection and semantic recognition based on the deep detection network. Typically, the extraction of nameplate text is performed after detection, followed by recognition.

The extraction of nameplate text in the "detection-recognition" task framework must take into account both accuracy and real-time performance. Various studies propose solutions for conventional text detection and recognition. For example, one study uses the VGG-16[8] network to extract features from the input image, and integrates multiple technologies to achieve text label detection. Another study proposes a special neural network based on the CNN+softmax structure [9], which uses a grid generator to detect text areas in the input image. Another algorithm called FOTS reduces the workload of network training. Since the content of electric equipment nameplates is typically related to electric power, character context semantics is important. To achieve qualitative sorting of nameplate information, one study pre-processes the arrangement of candidate characters on electric equipment nameplates according to the combination rules of electric terms.

One study applied the TDRN model with attention mechanism for nameplate detection to improve text recognition accuracy [10], as described in literature. To enhance text processing efficiency, literature proposed a method for text sequence feature extraction by integrating CNN and probabilistic graphical models. Distribution network equipment generates a large number of meter information images containing fault defect texts, such as indicator panels, digital dials, hard pressure plates, pointer dials, and secondary screen cabinets, according to literature. Machine vision can intelligently read display or status information text, identify possible defects, and ensure comprehensive awareness of important equipment status, priority monitoring, and alarms. In detecting and recognizing pointer dial indications, literature increased the camera field of view ratio and eliminated image distortion caused by the deviation between the dial plane and camera plane through perspective transformation based on the CNN model. The application of machine vision in the field of distribution network engineering also involves personnel detection, which can be divided into two main aspects: face recognition and real-time counting of personnel, and detection of behavioral standardization of engineering personnel. For face recognition and real-time counting of personnel, deep detection networks are used to detect and recognize faces, and statistical analysis of the number of personnel is performed in real-time [11]. On the other hand, the behavioral standardization detection of engineering personnel requires the dynamic recognition of human behavior in specific scenarios. This involves the application of deep detection networks to identify specific behaviors and check them against established standards. Literature briefly discusses the key technologies involved in applying machine vision to substation panel cabinets from an engineering perspective, including the selection, training, and deployment of classic deep detection networks.

In distribution network engineering, face recognition technology is crucial for verifying personnel qualifications and tracking traffic statistics on construction sites. To improve the accuracy of face recognition, several studies have explored different methods [12]. One study provided an overview of face recognition technology, highlighting that face recognition systems usually rely on multiple modules such as face position detection, alignment, representation, and matching. Other studies compared the effectiveness of different loss functions in face recognition, with one proposing the Angular-Softmax loss function to address the small class distance and large intra-class distance of L-Softmax in personnel detection. The Angular-Softmax loss function [13] learns and distinguishes people's behavior characteristics and adds discriminant constraints on the hyperspherical manifold. The results showed that Angular-Softmax outperformed the L-Softmax function [14]. In some distribution network engineering scenarios, it is important to ensure that the number of construction workers meets the regulations. This requires counting the flow of people to check whether the number of people is within specifications [15]. However, existing detection algorithms may have false detection or missed detection problems. Literature improved the CN algorithm by adding the direction gradient histogram feature to enhance the robustness of the human target color and background illumination, effectively improving the detection accuracy of moving targets. Literature focuses on small target detection, moving target association matching, and two-way people flow statistics algorithm. It improves the shallow feature extraction of images based on the Faster R-CNN [16] and adds the motion trajectory prediction and tracking algorithm to enhance the accuracy of people counting in dense areas. In the context of distribution network engineering, human behavior detection is a crucial aspect that involves identifying specific behavioral features from multiple frames of images in dynamic videos [17]. Typically, the detection of personnel behavior includes checking if certain basic behavioral norms are being followed, such as whether the workers are wearing helmets, work clothes, and protective equipment correctly, if they are smoking illegally, or if they are within a safe distance (establishing a virtual safety fence), among other things. Additionally, remote audits are performed to ensure that personnel operations and processes are standardized.

In order to recognize safety equipment such as helmets, researchers have applied improved SSD and optimized YOLOv3 [18]. Literature proposed a method to detect the dress code of substation workers by adjusting the output layer structure of YOLOv5 [19] and using sample expansion and initialization module clustering preprocessing. For behavior detection, a 3D CNN model [20] was proposed in literature, which can directly extract features from the original input and achieve better performance in human behavior recognition accuracy compared with traditional methods. This model extracts features from both time and space dimensions in surveillance videos. Traditional methods often rely heavily on human experience for feature extraction, whereas the proposed 3D CNN can directly extract features from the original input without human intervention, thus improving accuracy.

Recognizing the normative behavior of engineers over time and space poses a challenge for personnel behavior detection. Literature reviewed the effectiveness of action behavior recognition based on 3D skeleton sequence data and pointed out that GCN is closest to the natural representation of human bones and joints due to its topological graph-based method. The Mesh Transformer proposed in has been proven to have relatively high performance in human behavior recognition datasets. For real-time monitoring of power grid maintenance personnel in safe passages, literature propose algorithm models to solve incomplete background contours and semantic segmentation problems. Literature suggests an improved mixture Gaussian model to verify whether there are video sets at a safe distance for power grid maintenance personnel, while literature proposes a PSPNet semantic segmentation model to effectively extract the external contours of personnel and safety passages in substation scenarios.

Equipment inspection

In distribution network engineering, equipment inspection is an important task that involves identifying different types of power distribution equipment, determining their current status, and detecting any defects or abnormal appearances. Common equipment types include busbars, transformers, switch cabinets, circuit breakers, insulators, crossarms, cables, and clamps. One example of equipment status identification is confirming the opening and closing status of a knife switch, while abnormal appearance detection involves identifying issues such as open switch cabinet doors, blocked cable cabinet entrances, and dirty equipment casings. To address the specific task of switch state detection, literature proposes a method that screens straight line segments based on switch edge features and combines it with deep learning through YOLOv3. For the target detection problem of specific equipment, literature builds a classification network based on deep learning and a meter terminal monitoring network, and uses a configuration matching and fault identification network to obtain the terminal face. In distribution network engineering, equipment inspection involves identifying different types of power distribution equipment, detecting defects in power distribution equipment, and identifying the current status of power distribution equipment. The detection of abnormal equipment appearance is also important, such as checking if the switch cabinet door is closed or the entrance to the cable cabinet is blocked. To detect the state of the switch, literature proposes a method based on fusion of straight-line detection and deep learning, where straight line segments based on switch edge features are first screened before network training and detection using YOLOv3. For detecting faults in meter terminals, literature trains a deep learning network by sending typical "no fault" and "faulty" pictures, enabling the identification of faults. Porcelain insulators and line damage can also be recognized through image recognition using a deep detection network, as shown in references. These studies utilize large datasets of image samples of different components, such as porcelain insulators, to classify and monitor different types of equipment and identify local abnormal damage of the line.

DISCUSSION

Efficiently applying deep detection networks to dynamic defect detection in distribution network engineering requires clarifying the key technical routes and incorporating practical experience from other fields. Future research can focus on sample library construction, deep detection network design, and automatic machine learning to construct a network architecture suitable for the field of distribution network engineering.

CONCLUSION

The deployment of deep detection networks in distribution network engineering should take into account the large number of edge-side devices available. Simply deploying the deep network on the edge side can lead to issues such as high-power consumption and delay. Therefore, a lightweight and compressed network should be built, and the algorithm model deployment plan should be optimized continuously to balance the complexity, accuracy, and efficiency of the network model.

Finally, subsequent research can focus on constructing a network architecture suitable for distribution network engineering defect detection using automatic machine learning, allowing the model to learn and detect parameters and network configurations without human intervention.

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ИНФОРМАЦИЯ ОБ АВТОРАХ / INFORMATION ABOUT THE AUTHORS

Fan Ke, Arizona State University, Phoenix, United States, kfan6@asu.edu

Huang Chen-Yu, Illinois State University, Chicago, United States

Liu Weijia, Trine University, Phoenix, United States

He Kun, Illinois Institute of Technology, Chicago, United States

Shi Bin, University of Chinese Academy of Sciences, Chengdu, China

Wu Yanyou, Trine University, Phoenix, United States

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