Detection of High Voltage Transmission Lines: A Survey and Perspective

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Abstract. With the development of the national economy, the demand for electricity in various industries is expanding. It is necessary to ensure the safe operation of the high voltage transmission line. How to prevent and detect natural disasters and accidents that endanger transmission lines in a timely manner has become an important basic work to ensure power supply. Identifying high-voltage transmission lines first requires mathematical modeling of high-voltage transmission lines. Based on the mathematical model constructed, the image processing method is used to remove the blurred images in the images and restore the true background of the images. The establishment of mathematical models for high-voltage transmission lines has been relatively complete. This paper focuses on the analysis of existing methods for automatic identification and localization of foreign bodies on transmission lines and the existing research on deblurring, de-fogging, image denoising, image enhancement, etc. method. With the rapid development of deep learning, there are more and more methods for identifying high-voltage transmission lines and image restoration. More people will be engaged in this research in the future.

Keywords: Transmission line · Image restoration · Deep learning

1 Introduction

Images are the foundation of human face vision, and they give people a concrete and intuitive effect. Data digitization includes two parts: sampling and quantization. Digital image processing is the process of converting image signals into digital formats and using computers for processing and processing. Image restoration is an important issue in image processing, and it is of particular significance for improving image quality. The key to solving this problem is to establish a corresponding mathematical model for the degradation process of the image, and then obtain the restoration model of the image by solving the inverse problem and make a reasonable estimate of the original image.

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Image artificial intelligence processing can solve a series of hidden danger identification problems such as drones, video surveillance, and image surveillance. It is of great significance to improve the level of transmission management and personnel quality and efficiency. It also responds to the national and national network artificial intelligence development plans. Based on the analysis of this paper and the summary of existing methods, the foreign line and fault detection methods of transmission lines based on deep convolutional neural networks are analyzed and summarized.

2 Target Detection Methods

2.1 R-CNN

R-CNN uses AlexNet's network architecture and uses the Selective Search technology to generate Region Proposal. R-CNN is pre-trained on ImageNet, then fine-tune is performed on the PASCAL VOC dataset using mature weight parameters, then features are extracted using CNN, and then a series of SVMs are used for category prediction. Finally, R-CNN's bbox position regression was inspired by DPM and trained a linear regression model. The semantic segmentation of R-CNN uses CPMC to generate Region. Since RCNN comes earlier, it is not the best target detection model and semantic segmentation model.

2.2 SPP-net

The biggest improvement of SPP-net for R-CNN is that the feature extraction step has been modified, and other modules are still the same as R-CNN [12]. Feature extraction no longer needs to pass through the CNN for each candidate region. It only needs to input the entire image to the CNN. The ROI feature is directly obtained from the feature map. Compared with R-CNN, the speed has increased by a hundred times [5]. The shortcomings of SPP-net are also obvious. The conv layer in CNN cannot continue training when fine-tuning. It is still the framework of R-CNN.

2.3 Fast R-CNN

Sometimes, good results are not necessarily all original [17]. Fast R-CNN is a good illustration. SPPnet's pooling thought has been simplified and promoted on Fast, and author rbg further based on R-CNN [8]. The detection frame regression is integrated into the neural network, which makes the training test rate of Fast greatly improved.

2.4 Yolo

The core idea of YOLO is to use the whole graph as the input of the network, directly returning to the output layer and the position of the bounding box and its associated category [11]. The faster-RCNN also uses the entire graph as input directly, but the fast-RCNN uses the idea of RCNN's proposal + classifier as a whole, except that the steps to extract the proposal are implemented in CNN, while YOLO uses direct The idea of returning YOLO is not good for objects that are close to each other, and there is a small group detection [15]. This is because only two boxes are predicted in one grid and belong to only one category. The generalization ability is weak when new uncommon aspect ratios and other conditions occur for the same type of object. Due to the loss function problem, the positioning error is the main reason that affects the detection effect. Especially the handling of large and small objects has yet to be strengthened.

2.5 SSD

By comparing the network structure of SSD and YOLO, we can find that the advantage of SSD is that the default box generated by it is multi-scale [9]. This is because the feature map of the default box generated by SSD is not only the last layer of CNN output, but also the utilization. Compare the default box generated by the shallow feature map. Therefore, SSD detection of small targets will certainly be better than YOLO v1 (small targets almost disappear after high-level convolution). At the same time, because the multi-scale default box generated by SSD must have a higher probability to find a candidate box that is closer to Ground Truth, the stability of the model is definitely stronger than YOLO (YOLO's bounding box is very few, only 98, if Far from the GT, then the linear regression of the modified bounding box is not established, and the model may run when training). However, the number of candidate frames for SSDs is the highest among the three classic networks, with 8732, so it should be slower when training [9].

2.6 Yolov2

Although YOLOv1 has a fast detection speed, its detection accuracy is not as good as that of R-CNN. YOLOv1 is not accurate enough in object localization and has a low recall rate. YOLOv2 has proposed several improvement strategies to improve the positioning accuracy and recall rate of the YOLO model, thus improving mAP. YOLOv2 follows a principle in the improvement: maintaining the detection speed, which is also a big advantage of the YOLO model. It can be seen that most of the improved methods can significantly improve the mAP of the model.

2.7 Yolov3

Yolov3 solves the problem of difficult identification of small objects on the basis of v2, and is by far the most accurate framework for target detection.

2.8 Centernet

CenterNet's "anchor" only appears at the current target's position instead of the entire picture, so there is no such thing as a box anchor larger than a positive anchor, and there is no need to distinguish whether the anchor is an object or a background. Because each target corresponds to only one "anchor", this anchor is extracted from the heatmap, so no NMS is needed to filter the output resolution of CenterNet. The downsampling factor is 4, which is compared to other target detection frameworks. Smaller (Mask-Rcnn is at least 16 and SSD is at least 16). In general, the CenterNet structure is elegant and simple. It directly detects the center point and size of the target and is truly anchor-free.

3 Image Restoration Methods

Image restoration technology is a very important type of processing technology in the field of image processing. Similar to other basic image processing technologies such as image enhancement, it is also aimed at obtaining a certain degree of improvement in visual quality. The difference is that the image restoration process is actually An estimation process needs to restore the degraded image according to some specific image degradation models. In short, the process of image restoration is to improve the quality of degraded images, and to improve the visual improvement of images through the improvement of image quality. As there are many factors causing image degradation and their properties are different, there is no unified restoration method at present. Many researchers have adopted different degradation models, processing techniques and estimation criteria according to different corresponding physical environments, thus obtaining different restoration methods.

3.1 Deep Learning Method

Some scholars propose a six-layer convolutional neural network [14] for target recognition, and propose a localization algorithm based on output map information according to the characteristics of the transmission line itself. Firstly, the sliding window [3] method is used to make the convolutional neural network recognize each window of the input picture and obtain the output picture. Then, the output picture is binarized and opened, and finally the corresponding target is located according to the output picture information. In the process of network training, the image enhancement algorithm is used to expand the captured image of the transmission line fault model, and a training set consisting of 17,000 picture blocks and a detection set composed of 4000 picture blocks are obtained, which are used for network training and network detection. The set correct rate is 88.68% in the 125 position detection pictures, the transmission lines and related faults in 91.2% of the pictures can be detected. The experimental results show that in the picture with complex background, the deep learning algorithm can accurately identify [13] and locate the transmission line and its faults, and improve the versatility and applicability of the detection algorithm. It has practical significance for improving the detection efficiency of transmission line faults and improving the detection accuracy.

3.2 Method Based on Aerial Photography of Drone Control

Channel a priori is also a sparse priori that is manually designed by static statistically blurred images and sharp images. Different from the gray feature and the gradient feature of the direct statistical image, the channel prior is the pixel passing through the statistical channel. In 2009, He first proposed a dark channel prior and used it in image defogging, which made a breakthrough in image defogging [4]. An image dark channel means that the pixel value of at least one channel in the channel of the color image of the image block approaches zero. In 2016, Pan et al. first proposed applying the dark channel prior to the image deblurring field, pointing out that the clear image has a more sparse dark channel value than the blurred image, establishing dark channel sparsity.

3.3 Deblurring Algorithm Based on Edge Estimation

The core idea of blind deconvolution algorithm based on edge estimation is to estimate the image with large edge and small edge suppressed explicitly through some filtering and image enhancement algorithms, and then estimate the fuzzy kernel based on these significant edges [6]. The algorithm based on edge estimation is fast and has been proved to be very effective in practical application, but it is difficult to analyze, because it is not based on the model through optimization, but through some combination of heuristic steps [10].

The reason why the blind deconvolution algorithm based on edge estimation can successfully estimate the fuzzy kernel is that it can estimate the large scale edge in the image and suppress the small edge. The large scale edge is more beneficial to the estimation of the real fuzzy kernel, while the small edge plays an opposite role [7]. A bilateral filter is used to extract the large scale edge of the image and the extracted edge image is used for fuzzy kernel estimation.

3.4 Image Deblurring Based on Richardson-Lucy

Aiming at the ringing effect of RL algorithm, a new image deblurring algorithm based on RL was proposed, and Yuan's Gain Map was introduced in the iterative process, which effectively suppressed the ringing effect of the flat area and further amplified the image noise, and kept the details of the image [19]. At the same time, the effect of different parameter selection of the gain graph on the defuzzing result is discussed [16]. Experimental results show that the algorithm is effective in suppressing the ringing effect, preserving the image details, and recovering the fuzzy image with noise [20].

3.5 Image Deblurring Combined with Total Variation and Fractional Total Variation Model

In order to recover more details and texture information from fuzzy images, a digital image deblurring method based on combined total variation (TV) and fractional order total variation (FOTV) models is proposed [2]. The fuzzy image is decomposed into smooth region, convex edge and texture by the global gradient extraction method, the smooth region and convex edge are constrained by the full variation model, the details are constrained by the fractional order full variation model, the de-fuzzy convex optimization model is established, and the variable splitting and alternating direction method is used to quickly solve the model [1]. Experimental results verify the validity and rapidity of the model and algorithm [18].

4 Discussion

The safe operation of transmission lines is closely related to our daily lives. The country also invests a lot of money every year to ensure the normal operation of the power grid, but the transmission lines are high-voltage lines, and the cost of manual operations continues to increase and risks continue to increase. The perspective of artificial intelligence analyzes methods that can reduce human risks and provide guarantees for the development of the national economy.

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