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Survey of power line detection algorithms for aerial images based on machine vision

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Abstract

In order to avoid the helicopter crashing into the overhead power line when flying at low altitude, the common method is to use the power line collision avoidance system that based on machine vision. The power line detection algorithms in these systems can be divided into two categories, the detection algorithm based on traditional image processing and the detection algorithm based on deep learning. The advantages and disadvantages of different algorithms are obtained after the comparing and analyzing of all the common algorithms of the two categories, respectively. The algorithm simulation shows that the power line detection algorithm based on deep learning has more development advantages in practical application.

Keywords

Power line detection, image processing, computer vision, deep learning.

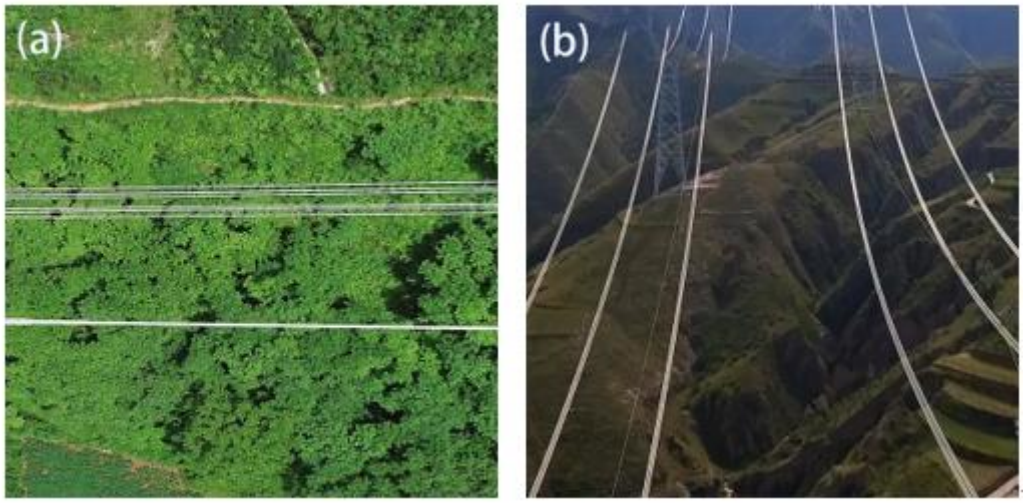
1. Introduction

UAVs or helicopters are often used to perform tasks including power line inspections and low-altitude search and rescue in the wild. When flying at low altitudes, the probability of accidents is greatly increased due to the complex flight environment. The common obstacle that causes low-altitude flight accidents is the power line. . Bright aviation marking balls will be used to improve the visibility of power lines, but the installation of aviation marking balls has not been widespread. At the same time, due to the complex environment of the power line and the possibility of encountering various weathers during flight, it is often difficult for pilots to observe the power line with the naked eye. Therefore, it is very important to design a power line detection and collision avoidance system for the aircraft. Since there are generally cameras on airplanes, they often use their own high-definition cameras to implement machine vision-based power line collision avoidance systems, and a very important step for the system is to quickly and accurately detect power lines from aerial images. This paper compares power line detection algorithms from the perspective of processing methods, and comprehensively divides them into two categories, namely detection algorithms based on traditional image processing and detection algorithms based on deep learning. The advantages and limitations of the algorithms are analyzed, and based on The development trend of image processing power line detection technology provides reference for relevant scientific researchers.

2. Power lines in optical aerial images

The background of the image obtained by aerial photography of aircraft is mostly ground-based, and the angle is from a top view or a squint angle. The shape of power lines in aerial images is generally straight or curved, as shown in Figure 1. Therefore, the problem of detecting power lines from aerial images can be transformed into a problem of detecting linear structures in the image, but the background in aerial images is the ground. It contains more linear structure

information. To detect the power line correctly and quickly, it is necessary to effectively filter out this type of noise structure.



(a) Linear power line image; (b) Curved power line image
Figure 1: Aerial image of power line

3. Detection algorithm based on traditional image processing

The power line detection algorithm based on traditional image processing methods, the main idea is to design the detection algorithm based on the structural characteristics of the power line itself and prior knowledge. The general process of this type of algorithm is: first, the original image is enhanced to make the power line and background clutter more obvious; then through the edge detection algorithm, all the edge structures in the image are detected, and the edge binary image is obtained; finally, Filter out the noise according to the prior knowledge, and use the straight line structure detection algorithm on the edge map to extract the straight line in the image, then smooth the detection result, and finally detect the power line. The process is shown in Figure 2.

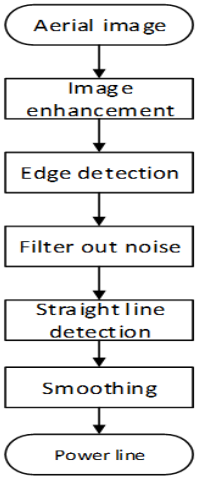


Figure 2: Flow chart of detection algorithm based on traditional image processing

3.1. Detection algorithm based on Hough transform

In view of the uniform linear structure of the power line, the Canny edge detection operator [1] and the Hough transform [2] are often combined to design the power line detection algorithm [3-9]. When the Canny edge detection operator is used to detect the image After the edge binary image, the Hough transform is used to represent the straight line that each edge point may pass through in the Hough space. Each point in the Hough space represents a straight line in the

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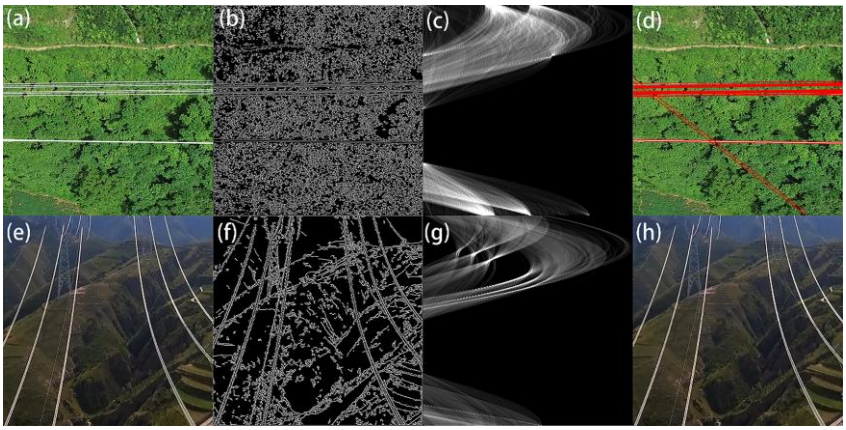
Cartesian coordinate system. Each edge point has all the possible lines that may pass through. A straight line is represented as a complete curve in the Hough space, and finally the intersection of multiple curves in the Hough space is calculated. This intersection is a straight line in the original image. The main steps of the detection algorithm based on the Hough transform are shown in Figure 3.

Based on the detection algorithm of Hough transform, it takes 0.95 seconds to process a 360×540 aerial image, and there is a misdetection of linear noise.

LI et al. [4] used a pulse-coupled neural filter to remove background noise and generate edge maps, and used a priori knowledge-based line clustering method to accurately measure the results in the Hough space, but the algorithm detection took too long; Candamo et al. [5] uses windowed Hough transform to track and detect power lines; Chen et al. [6] use Hessian matrix for edge detection, and propose a random Hough transform based on region segmentation, which improves certain accuracy and detection speed; Wang et al. [7] used Otsu to obtain high and low thresholds during edge detection, which effectively avoided manual parameter adjustment. In addition, the Hough transform improved by the fractional look-up table method greatly improved the detection speed. Finally, by analyzing the power line space information, Connect or filter the detected line segments; Aggarwal et al. [9] use a regularized form to combine prior information to enhance the performance of the line detector based on the Hough transform.



(a) is the original image of linear power line; (b) is the edge detection image of (a); (c) is the Hough transform image of (b); (d) is the final detection image of (a); (e) Curved power line original image; (f) is the edge detection image of (e); (g) is the Hough transform image of (f); (h) is the final detection image of (e)

Figure 3: Diagram of detection results based on Hough transform

The detection algorithm based on Hough transform can only detect linear power lines, but cannot detect curved power lines, as shown in Figure 3(d), and it is easy to detect linear noise. Although the related improved algorithm can filter out some background noise, It also increases the time-consuming and computational complexity of the algorithm.

3.2. Detection algorithm based on Radon transform

Radon [10] transformation is also a classic line segment detection algorithm [11-13]. Radon transformation is similar to Hough transformation for straight line detection. It also transforms the image into the parameter space and calculates the intersection point in the parameter space. The difference is that the Radon transform The grayscale image is used instead of the edge binary image. The transformation method uses line integral. The Radon transformation can detect a certain curved power line. The main step results of the detection algorithm based on the Radon transformation are shown in Figure 4 [11].

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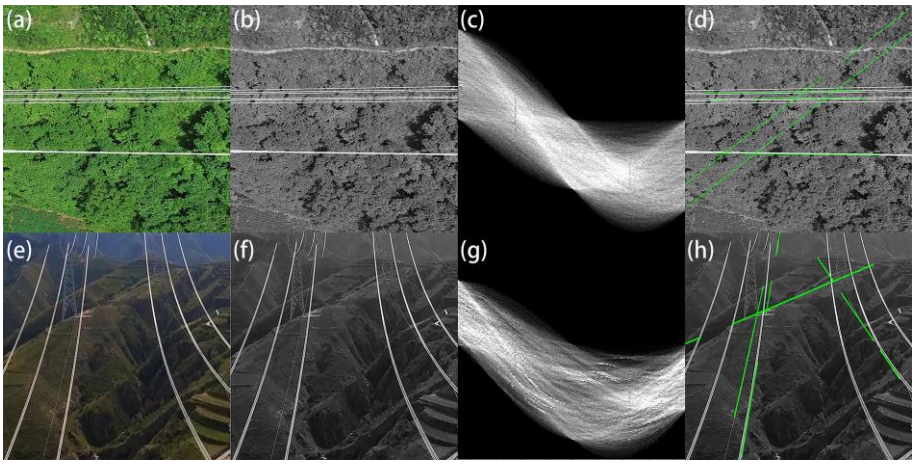
Based on the Radon transform detection algorithm, it takes 1.2 seconds to process aerial images of the same size. Although a certain curve-shaped power line can be detected, there are still too many false detections.



(a) is the original image of the linear power line; (b) is the gray image of (a); (c) is the Radon transform image of (b); (d) is the final inspection image of (a); (e) The original image of the curved power line; (f) is the gray image of (e); (g) is the Radon transform image of (f); (h) is the final inspection image of (e)

Figure 4: Diagram of detection results based on Radon transform

Yan et al. [11] used linear feature filters and ratio line detectors to extract power line pixels, then used Radon transformation to connect power line pixels into multiple line segments, and finally used grouping and Kalman filtering techniques to connect each line segment and smooth it into a complete line. Power line. Zhao et al. [12] used the improved Log operator (EDPF) algorithm to detect the edges of aerial images, with high recognition accuracy, but only considered the situation where the power lines traverse the entire picture in parallel and straight lines. The actual situation is more complicated; Chen et al. [13] Detect power lines from high-definition remote sensing images through Cluster Radon Transform (CRT).

There are some other methods [14,15], Lv et al. [14] extract ridge points through a controllable filter, perform connected component analysis according to the idea of region growth, and connect the ridge points belonging to the power line into a complete line . Zhang et al. [15] used the spatial correlation of power lines and proposed a power line measurement algorithm based on pole restriction.

3.3. Detection algorithm based on line segment detector

Lsd[16] and Edlines[17] line segment detectors are often used to design line segment detection algorithms [18-21]. When the two line segment detectors process 360×540 aerial images, they need 0.45 seconds and 0.02 seconds respectively. Both algorithms can extract the two types of power lines relatively completely, but there are a lot of linear structure noises. It still takes a lot of time to process and filter out these noises, and the algorithm design is complicated. The detection of the two algorithms is shown in Figure 5[16,17].

Yetgin et al. [18] used Edlines to extract all the complete curves in the image, and used the K-Means mean clustering method to filter out the curves that are not on the power line. This algorithm has high detection accuracy and is currently faster. Traditional algorithms, but cannot filter out noise curves that are roughly structured similar to power lines. Tan et al. [19] used Lsd to extract all line segments in the image, and used the statistical characteristics of all line segments to filter out the cluttered line segments that did not belong to the power line and form a series of line segment clusters. Finally, the least squares method was used to fit the line segment clusters to form some For a complete power line, the algorithm has high accuracy but slower speed. Lin et al. [20] combined the classic Ratio operator with the Ransac algorithm to

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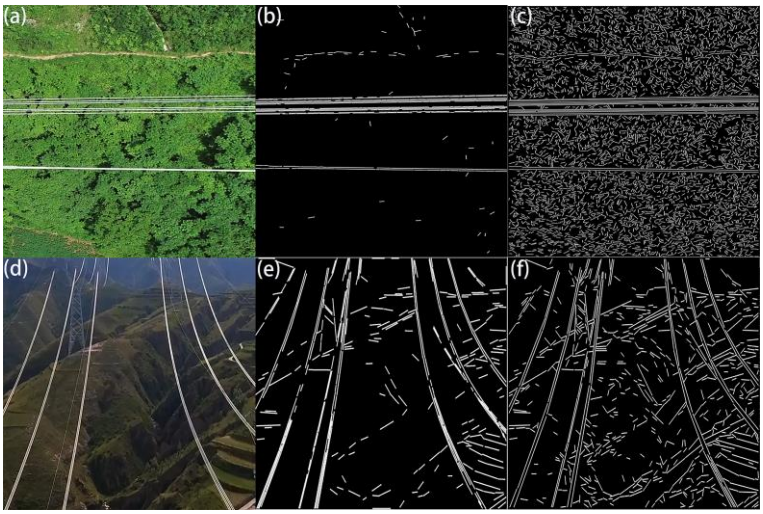
design a power line detection algorithm. Song et al. [21] used a zero-mean Gaussian filter (MF) and a first-order Gaussian derivative (FDOG) to calculate the edge map, and adopted a graph cut method based on graph theory for power line fitting.



(a) is the original drawing of the linear power line; (b) is the LSD detection diagram of(a); (c) is the EDLINES detection diagram of (a);) is the original diagram of the curved power line, (e) is the LSD detection diagram of (d), (f) is the EDLINES detection diagram of (d)

Figure 5: he detection result diagram based on the line segment detector

Although the performance of power line detection algorithms based on traditional image processing has been greatly improved in recent years; traditional algorithms are difficult to filter out noise similar to power line features, and this noise has a great probability of appearing in real scenes [14]. It is a problem that the algorithm itself only relies on the design of power line characteristics.

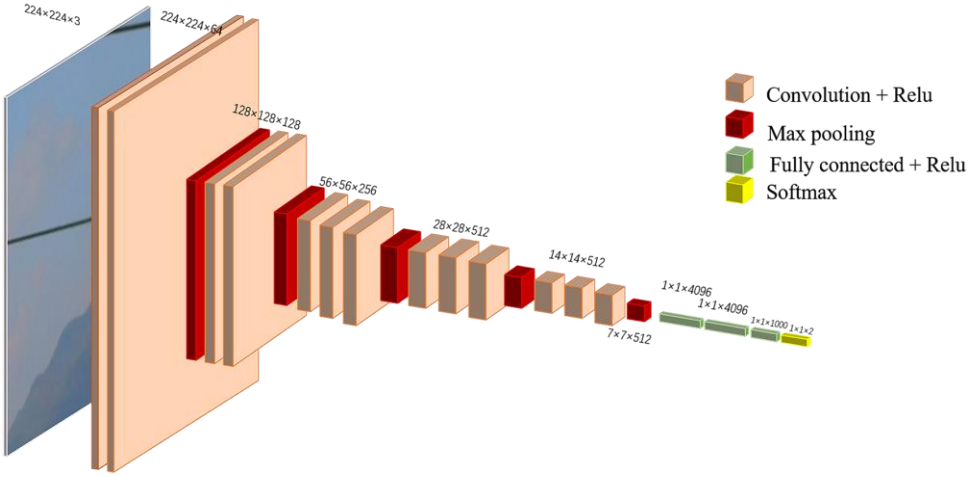


Figure 6: Schematic diagram of VGG16 volume integral network

4. Detection algorithm based on deep learning

In recent years, deep learning has become the main method to solve problems in the field of computer vision. When processing images, convolutional neural networks (CNN) are widely used in image feature extraction. CNN can extract both low-level features (detail features) and high-level features (semantic features), which makes up for the lack of image information used by traditional power line detection algorithms The problem. Therefore, in recent years, it is the main trend to apply CNN to the design of power line detection algorithms based on machine vision. Convolutional neural network VGG16 [22] is easy to be deployed on mobile platforms such as drones due to its simple structure. Many algorithms use VGG16 as the original model

for algorithm design. Figure 6 is a schematic diagram of a convolutional class network based on VGG16: using convolutional neural networks to extract features, and then using features for classification [22].

4.1. Classification technology based on deep learning for power line detection

The related technology of using convolutional neural network to classify images has been developed very mature. Convolutional neural network not only accurately classifies high-level targets with rich information, but also has better classification results for low-level targets with less information. At this stage, power line In the detection algorithm, the classification technology based on deep learning is only a step in the power line detection algorithm. It is used to filter out the area containing the power line and then perform the power line detection, which can reduce the algorithm calculation amount and speed up the calculation speed.

The main idea of the literature [23-26] is to divide the original image into many sub-regions, and divide the sub-regions into two types including power lines and excluding power lines through convolutional neural networks, and filter the sub-regions that do not contain power lines as noise. , Post-processing of sub-regions containing power lines. The difference is: Liu et al. [23] determine the area containing the power line by detecting the position of the power tower in the image, and then perform power line detection based on the power tower-line context; Li et al. [24] are dividing the original image into sub-regions When the pyramid division standard was proposed, the traditional line detection algorithm was used in the post-processing stage; Zhang et al. [25] used Faster-RCNN [26] to detect the power line area in the image, and proposed a tower based on the kernel correlation filter. Tracking strategy is used to track and detect power lines; different from the previous approach, Yetgin et al. [27] directly classify the original images, ignore the pictures without power lines, and design a saliency processing method for pictures containing power lines [28]

Image classification technology based on deep learning is applied to design power line detection algorithms. Compared with traditional detection algorithms, the performance has been improved to a certain extent, but most of its processing links are traditional processing methods that rely on prior knowledge. The algorithm design is complex and inefficient. It can't solve the actual needs well. Therefore, the latest power line detection algorithm designers are pursuing automated, simplified, and efficient algorithm design.

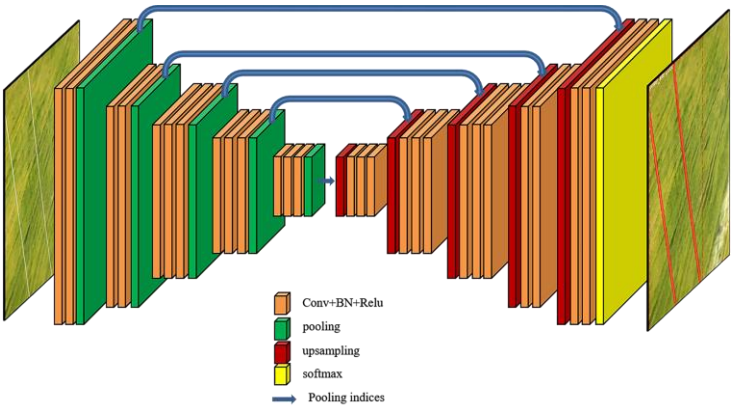


Figure 7: Schematic diagram of SegNet semantic segmentation network

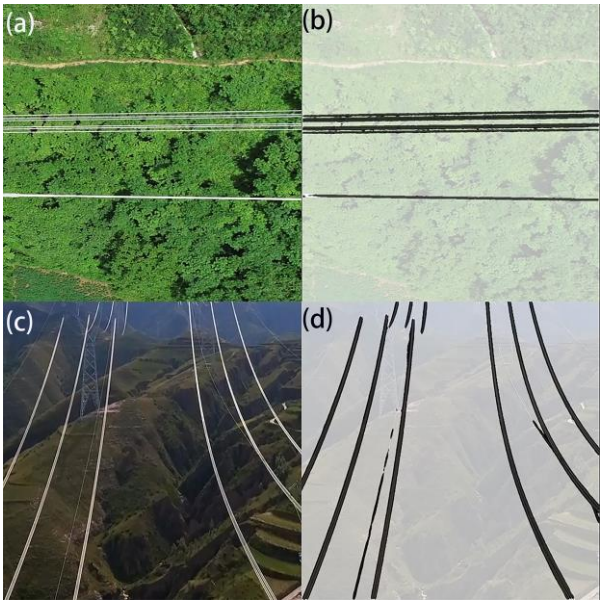
4.2. Segmentation technology based on deep learning for power line detection

The deep learning semantic segmentation technology represented by Full Convolutional Neural Network (FCN) [29] has been developed rapidly in recent years. Its end-to-end network structure is efficient and concise after training, without the need for manual adjustment of parameters, namely Can realize automatic processing of semantic segmentation tasks. The power line detection based on machine vision can also be regarded as a semantic segmentation

problem, and the semantic segmentation technology based on deep learning satisfies the latest power line detection algorithm design requirements. Therefore, the semantic segmentation technology based on deep learning is used to design The power line detection algorithm is the latest design idea.

As a representative work of deep learning semantic segmentation technology, FCN is often used as a basic network design power line detection algorithm. Figure 7 is a schematic diagram of a semantic segmentation network with a fully convolutional structure (based on SegNet implementation) [30]. Its network structure is: first volume Product, normalization and pooling operations are used to compress the original image for encoding, and then use upsampling and convolution to decode the encoded image.

Li et al. [31] added an attention mechanism based on spatial information on the basis of a fully convolutional semantic segmentation network to reduce the attention of the neural network to the background and improve the attention to the target. Zhang et al. [32] segmented the image, they did not perform pixel-by-pixel classification, but combined each feature layer with a weighted combination to generate a segmentation map. Choi et al. [33] proposed a method of weakly supervised learning using only image-level annotation data, and cleverly designed a recursive learning network training method, so that after the network is trained with image-level annotation data only, the algorithm effect and the use of pixel-level Data training is flat. Jenssen et al. [34] used artificially synthesized power line images as training data and proposed a fast single-shot line segment detector (LS-Net). Liu et al. [35] proposed to detect power lines as objects instead of segmentation, and the target detection network framework used was Faster R-CNN.



(a) is the original picture of the linear power line; (b) is the result of the VGG16-Unet test of (a); (c) is the original diagram of the curved power line; (d) is the VGG16-Unet test result diagram of (c)

Figure 8: Test result diagram based on Vgg16-Unet

The Vgg16-Unet semantic segmentation network represents the power line detection algorithm based on deep learning. Its calculation time only takes 0.056 seconds, and there is no linear structure noise, and no complicated post-processing operations are required. The detection effect in Figure 8[36]. The detection algorithm based on deep learning has better results. However, the data set is the main factor restricting the development of this algorithm. At present, power line data is relatively scarce, and manual data pixel-level labeling is a difficult task.

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5. Algorithm comparison analysis

The hardware used in this computer experiment is I3-9100F (CPU), GTX1060 6GB (GPU), and the picture size is 360×540. Two types of power line detection experiments have been performed on five arithmetic methods. The detection results are shown in Table 1. It can be seen that most of the detection algorithms based on traditional image processing need to spend a lot of calculation time, but in practice, it must reach a speed of processing 15 frames per second at least, that is, the processing time of a single image is less than 0.067 Seconds, only the Edlines line segment detection algorithm and the Vgg16-Unet convolutional neural network meet the requirements, and the Edlines algorithm and other traditional algorithms have the problem of detecting linear noise. The design of complicated post-processing algorithms in order to filter out the noise will inevitably reduce the operation Speed, and different post-processing algorithms should be designed according to aerial images in different regions, so the generality is not strong. The detection algorithm based on deep learning only needs one training to achieve better detection results, and there is no need to design post-processing algorithms. It has strong versatility. However, it requires more power line data to train the neural network. It is too expensive to collect data by plane or helicopter, and the Generative Adversarial Network (GAN) [37] that has emerged in recent years can be used to artificially synthesize power line data, which is expected to solve the problem of insufficient power line data.

Table 1: Comparison table of algorithm experiment results

Agorithm	Detection speed	Straight power line	Curvilinear power line	Post-processing
Canny-Hough	0.95s	Full detection but noisy	Can't detect	Need
Radon	1.2s	Partially detected but noisy	Partially detected but noisy	Need
Lsd	0.45s	Full detection but noisy	Full detection but noisy	Need
Edlines	0.02s	Full detection but noisy	Full detection but noisy	Need
Vgg16-Unet	0.056s	Full detection with not noise	Full detection with not noise	Not need

6. Conclusion

In summary, the power line detection algorithms based on machine vision at this stage are divided into the following two categories:

(1) Detection algorithm based on traditional image processing, the algorithm design is simple, the design does not require a large amount of data, the calculation speed is slow, and the detection result will contain linear structure noise.

(2) Based on the detection algorithm of deep learning, the calculation speed can exceed 15 frames per second, and linear structure noise will not be detected, but a large amount of data is required for training, and better hardware equipment support is required. With the improvement of hardware performance , And the emergence of various data enhancement technologies, power line detection algorithms based on deep learning have attracted more and more attention.

Acknowledgements

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