POWER LINE DETECTION VIA BACKGROUND NOISE REMOVAL

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ABSTRACT

Tiny target detections, especially power line detection, have received great attention due to its critical role in ensuring the flight safety of low-flying unmanned aerial vehicles (UAVs). In this paper, an accurate and robust power line detection method is proposed, wherein background noise is mitigated by an embedded convolution neural network (CNN) classifier before conducting the final power line extractions. Our proposed method operates in three steps: 1) extract edge features of power lines from a testing image, 2) employ a CNN classifier to remove the background noise, 3) use a Hough-Transform (HT) based fine-selection module to locate power lines. Comprehensive experiments demonstrate the superiority of the proposed method, compared to the state-of-the-art methods.

***Index Terms*—** power line detection, image processing, machine learning, classification, edge feature

I. INTRODUCTION

With the development of modern aircraft design technology and the opening of low airspace, unmanned aerial vehicles (UAVs) have been more frequently applied in a variety of low altitude operations. However, the safety of such operations are gravely endangered by several hazards, especially power lines, in the low flying environment [1]. With the objective of minimizing the damages result from the collision between UAVs and power lines, it is vital to develop reliable power line detection techniques thus enable the UAVs to detect power lines during flight by itself.

However, power line detection is faced with many challenges. First of all, common difficulties such as camera jitters, image blur, color intensity and weather variations could as usual affect the accuracy of detection. Whats more, compared with other targets such as buildings and tall trees, power lines are uniquely challenging because the lack of significant features, complete structure, and adequate pixel ratio in the image. More importantly, cluttered background containing other linear objects would further complicate the detection by introducing troublesome noises. How to reliably handle the noise has remained insurmountable.

To solve the aforementioned challenges, lots of power line detection algorithms have been proposed, which can be divided into two categories. The first category includes methods relying on the linear features of the power line [2, 3, 4], which is therefore referred as line-based method. In particular, in [2] linear features are extracted by a Gaussian model. Differently, Song, B. et.al [4] obtained power line fragments using the matched filter and Gaussian first order derivative, then the fragments are combined into a complete power line according to the graph cut model. The other category of methods detects power lines on basis of the spatial correlation [5, 6, 7, 8], and is known as the correlation-based method. For this category, the parallel relationship between the power lines [5, 6] or the connection relationship between power lines and the pylon [7, 8] is utilized to facilitate the detection. Specifically, Zhang et al. [8] detect power lines by associate the lines with the pylon using their spatial correlation. Comparatively speaking, the correlation-based methods outperform the line-based methods in resisting the background noises. However, such methods are not always feasible for the fact that most of the power lines in images have no parallel relationship and the pylon does not always exist in aerial video.

As a result, for the purpose to design a noise-resilient method with high applicability, in this paper a novel CNN-aid power line detection is proposed. Considering the great influence brought by the background noises during the feature extraction, we employed a coarse-to-fine strategy to exclude the impact of background noise before providing reliable detection outputs. In specifics, edge feature map is firstly generated in the beginning. Afterwards, in the coarse stage, most of the noise is excluded from the feature map via the CNN-based patch classification. Subsequently, in the fine stage, the power line segments are extracted using a Hough transform from the remaining of the coarse stage.

The rest of the paper is organized as follows: the proposed method is described in Section II. Section III presents the experiment results. Section IV summarizes the paper.

II. METHODOLOGY

A. Basic Idea

The accuracy of power line detection is greatly affected by the background noise in the image, which constantly disturbs the feature extraction of the power lines. For this reason, how to effectively remove the influence of the background noise is the key to improve the accuracy of the power line detection. Nonetheless, the nature of the noise in the background can be highly diversified, therefore invalid the effort to clear it all at one shot. Consequently, we amount to adopting a detection method that follows the coarse-to-fine strategy. In particular, the detection starts with generating a map by extracting edge features. Subsequently, the coarse selection process eliminates the majority of the noise from the edge feature map, while only left out the ones share high approximate features with the power lines. Afterwards, the fine selection process deliberately picks out the power lines that are concealed among all the remaining edge feature.

B. System Design

Fig. 1 illustrates the framework of the proposed method. The whole system consists of three components. The first component is the edge feature detector, which is used to extract edge features from the image to generate the candidate target set. This set is also referred as the edge feature map, which contains both power lines edge features and background noise. The second component is a coarse selector based on CNN, which serves the purpose of eliminating the small noise patch in the edge feature map. Most of the background noise can be filtered out after this coarse selection, yet there is still a small amount left over. In order to obtain more accurate information of the power lines, the third component - a fine selection module is employed. The fine selection module is essentially a line segment detection system based on Hough transform. Finally, the power line segments are combined with the original image to display the position of the power lines.

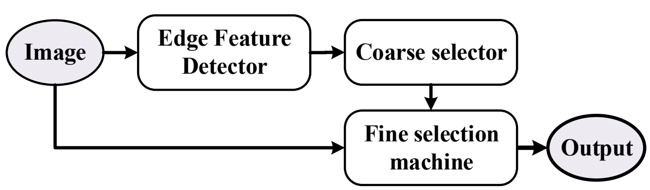


Fig. 1: The framework of the proposed power line detection.

C. Design of Edge Feature Detector

Theoretically, the edge gradient directions of the power line in the image are not fixed. It is difficult to extract the complete edge features from a single direction. As a result, it is reasonable to calculate the edge gradient from multiple directions (M directions in our experiments) instead of from only one. Accordingly, an edge feature map that contains abundant information can be established by iteratively computing the sub edge features from various directions.

In order to construct the edge feature map, we first consolidate the edge information by applying the edge-enhancing method described in [9]. Subsequently, we choose the steerable filter G_i designed by three order derivative of Gauss function [10] as our base filter to extract edge feature. Based on G_i, the edge feature extraction is carried out as following formulas.

$$I_i = G_i \otimes I \qquad i = 1,2,3,...,M \tag{1}$$

$$E_i = \sqrt{E_{i-1}^2 + I_i^2} \quad (E_0 = \mathrm{O}) \quad i = 1,2,3,...,M \tag{2}$$

I indicates the original image; I_i is a sub edge feature map in the i-th direction; E_i is obtained through iterative calculations. Specifically, $(E_0 = \mathrm{O})$ is the initial stage where O is a zero matrix. M is the number of directions and defined as $M = 360/\Omega$, where Ω is the interval between the directions.

The detailed process of edge detection is described in Fig. 2. At the beginning, the original image I is processed by the first base filter G_1 in the direction of θ_1 to yield the sub edge feature map I_1. Subsequently, the second base filter G_2 processes the original image I in the direction of θ_2 and result in the sub edge feature map I_2. Here E_1 and E_2 is calculated according to formula (2). Such an iteration continues until all the M directions are considered. The result of the last round of iteration is the edge feature map of the power line. The

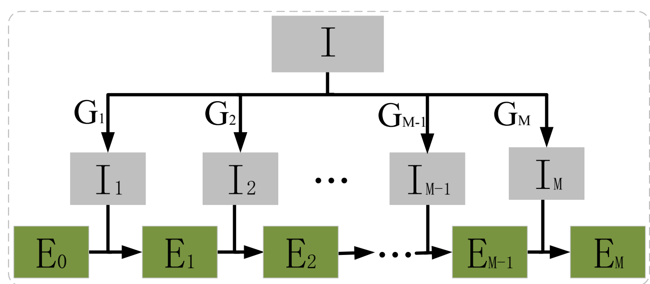


Fig. 2: The process of edge feature extraction.

filter function G_i for each direction θ_i is calculated according to the following formula.

$$\begin{aligned} G_i = K_a(\theta_i) * G_0 + K_b(\theta_i) * G_{\pi/4} + \\ K_c(\theta_i) * G_{\pi/2} + K_d(\theta_i) * G_{3\pi/4} \end{aligned} \tag{3}$$

Where G_0, $G_{\pi/4}$, $G_{\pi/2}$, $G_{3\pi/4}$ is the three order derivatives of Gauss in direction 0, $\frac{\pi}{4}$, $\frac{\pi}{2}$ and $\frac{3\pi}{4}$, which serves as the basis functions for constructing the filter function G_i [10]. And the coefficients $K_a(\theta_i)$, $K_b(\theta_i)$, $K_c(\theta_i)$, $K_d(\theta_i)$ in the direction of θ_i are defined as follows.

$$K_a(\theta_i) = \cos^3\theta_i \tag{4}$$

$$K_b(\theta_i) = -3 * \cos^2\theta_i * \sin\theta_i \tag{5}$$

$$K_c(\theta_i) = \ 3 * \cos\theta_i * \sin^2\theta_i \tag{6}$$

$$K_d(\theta_i) = -\sin^3\theta_i \tag{7}$$

D. CNN Classifier

In the field of deep learning, CNN is one of the most frequently used algorithms for classification. It has been applied to various classification scenarios and achieved appealing results [11, 12, 13, 14]. In our method, a CNN with five hidden layers have been employed to classify the patches containing edge features of the power lines and the background noises. The network structure of CNN adopted in our method is shown in Fig. 3. And the configuration parameters of CNN are determined according to the constant trial and error in the training phase. The layer #I input the patches of the testing

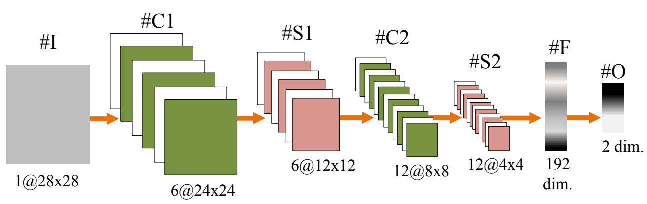


Fig. 3: The structure of the CNN network employed by the proposed method.

image. The size of the patch is set to be 28*28px. Some of the patches are noises, which need to be ruled out, and the others are useful edge features of the power line.

The layer #C1 and #C2 are the convolution layers, #C1 contains 6 feature maps and #C2 contains 12 feature maps. #S1 and #S2 are the down sampling layers, also called polling layers. They are used to maintain certain invariance (rotation, translation, scaling, etc.) for feature maps by means of the mean-pooling, max-pooling or stochastic-pooling.

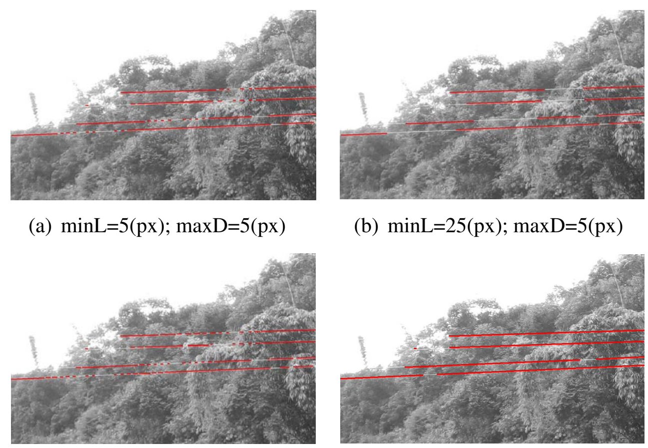
The layer #F is the full connection layer, all the nodes in the #S2 are connected into a vector. And then the vector is sent to the layer #O. By analyzing the vector, we can determine whether the input patch is the edge feature of the power lines or the background noise. More specifically in the proposed method, the value of each dimension of the vector represents the probability that the input patch belongs to a particular class. Such as, from the vector $\vec{O} = (0.96, 0.04)$, we can deduce that the input patch belongs to the first class (The first class is the edge features of the power lines in our experiments).

For CNN, insufficient training data is likely to cause overfitting problem. To overcome such a situation, in our experiments, a large number of power line images, including 300 raw videos and 10,000 raw color images, are collected. Totally 45,000 positive patches and 60,000 negative patches are extracted from these raw data and used to build a sufficient training data set.

E. Hough Transform

Hough transform is of great importance for detecting the shape of the object [15]. An improved Hough transform-Gradient based progressive probabilistic Hough transform GPPHT [16] is used as our fine selection module to extract power line segments from the background noise which cannot be eliminated by patch classification.

GPPHT algorithm first extracts the longest, most significant line segment, then the second longest and significant one, and continues looking down until all the points in the edge feature map are traversed. There are two parameters which play important roles in controlling the computational results in the process. The first parameter is the threshold minL, which controls the length of the line segment. Only the line segment length larger than minL can be extracted. The second parameter is the threshold maxD, which limits the maximum distance between two points that can be connected. In other word, points can be connected in a line only when the distance between them is less than the maxD. By adjusting these two parameters, we can get different detection results as in Fig. 4.



(a) minL=5(px); maxD=5(px)
(b) minL=25(px); maxD=5(px)
(c) minL=5(px); maxD=2(px)
(d) minL=5(px); maxD=25(px)

Fig. 4: The result of GPPHT under different minL and maxD.

III. EXPERIMENT RESULTS AND EVALUATION

A. Performance of the Proposed Method

The experiments are conducted in three different scenes as demonstrated in Fig.5 As shown in Fig.5 (a1)∼(c1), after edge feature detection, there are still a lot of background noise left in the power lines edge features maps. And in Fig.5 (a2)∼(c2), we can clearly see that most of the remained background noise has been eliminated by conducting patch classification with CNN. Fig.5 (a3)∼(c3) demonstrate the line segments extracted by GPPHT. At last, the detecting results are combined with testing image to indicate the location of the power line in the image (Fig.5 (a4)∼(c4)).

Not limited to these three scenes, we also performed experiments in other scenes and made a detailed comparison between the proposed method and other typical power line detection methods. The comparison results can be found in Section III-B.

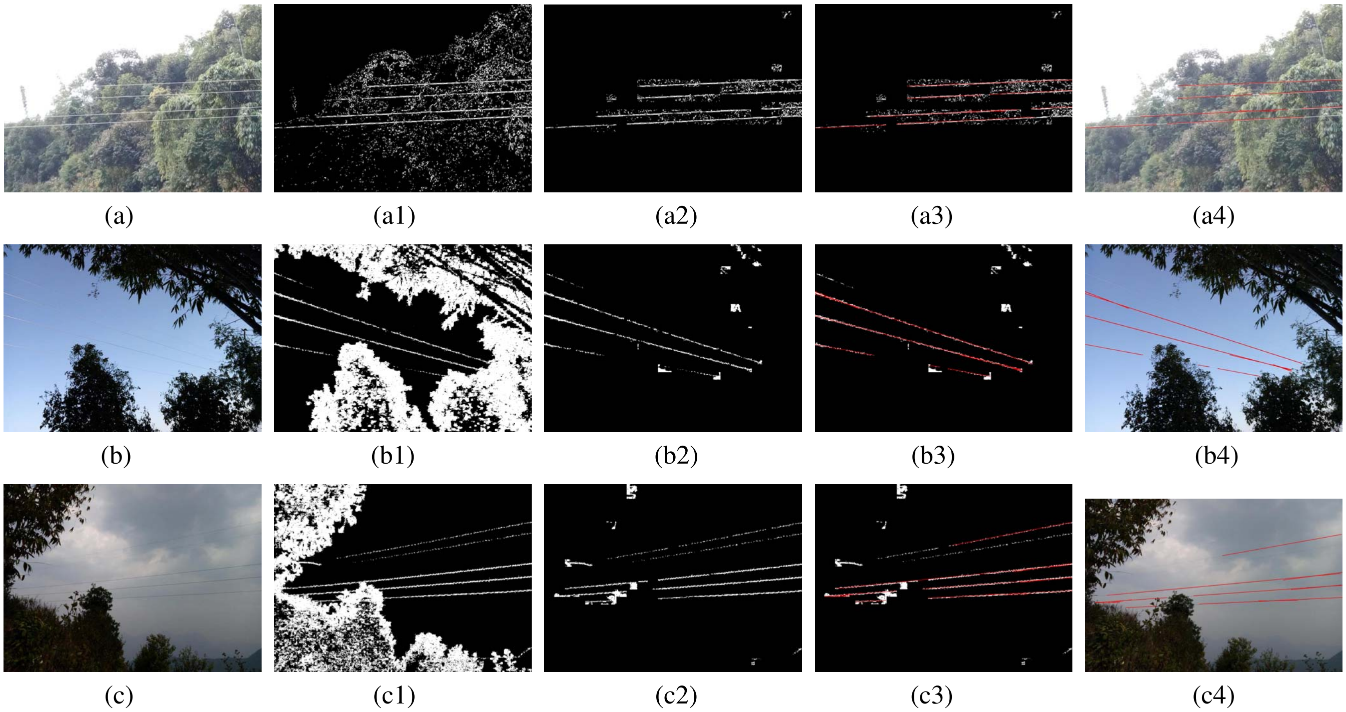


Fig. 5: The performance of the proposed method. (a)$\sim$(c) are the testing image; (a1)$\sim$(c1) are the edge feature maps; (a2)$\sim$(c2) are the results of the classification; (a3)$\sim$(c3) are the line segments extracted by GPPHT; and (a4)$\sim$(c4) are the output.

B. Comparison with Other Methods

In this work, two widely applied power line detection methods are selected to compare with the proposed method. The first one is a Gaussian Model (GM) based power line detection method [2]. Such a method uses GM to approximate the intensity profile of a line and its surroundings. The other one is based on the spatial contexts (SC), which relies on a spatial correlation model describing pylon-line and line-line relationships to realize power line detection [7].

The comparison results involving three performance indexes, precision rate (PR), missing rate (MR) and false alarm rate (FAR), are demonstrated in Table 1.

Table 1: The performance of the methods.

Methods	PR (%)	MR (%)	FAR (%)
GM	84.70	12.34	18.39
SC	89.21	**8.50**	17,96
Proposed	**91.14**	10.61	**15.88**

In Table 1, the best result of each index is marked in bold format. It is clear that our method excels in precision rate and false alarm rate among the three methods. The SC based method has the lowest MR due to the presence of pylon in the scene, which helps improve its performance. After a comprehensive comparison, it can be seen that the proposed method is more effective overall.

IV. CONCLUSION

In this paper, a novel power line detection method is proposed. Different from traditional methods, here a CNN is employed to help eliminate the background noise via patch classification. On this basis, the fine selection module is able to extract most of the power line segments from the selected edge feature map. In this way, the precision rate can be greatly improved and the false alarm rate reduced significantly.

Nonetheless, several issues are still open for further study. In this work, the patch classification is based on the extracted edge features. In our future work, we will focus on applying patch classification to raw images.And take the spatial relationship between the power lines and the surrounding objects into consideration to improve the detection rate.

ACKNOWLEDGMENTS

This paper is supported by the National Natural Science Foundation of China (Grant No. 91538204), the National Science Fund for Distinguished Young Scholars (Grant No. 61425014) and the Foundation for Innovative Research Groups of the National Natural Science Foundation of China (Grant No. 61521091).

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