Research on Target Tracking Technology of UAV in Distribution Network Based on Deep Learning

Dai Wan[1(✉)], Simin Peng[1], Miao Zhao[1], Yingying Yi[2], Hengyi Zhou[1], WenHui Mo[1], and Jingyang Wang[3]

[1] State Grid Hunan Electric Power Company Limited Research Institute, Changsha 410007, China
280241509@qq.com
[2] Changsha Tax Service, Changsha 410000, China
[3] China Three Gorges University, Yichang 443000, China

Abstract. With the rapid development of unmanned aerial vehicle (UAV) technology, the application of UAV patrol inspection in the power grid side is becoming more and more popular. At present, the application of UAV inspection technology in the power transmission profession has become increasingly mature. However, there are still many problems in the application of UAV inspection technology in power distribution specialty. First, the operation environment of distribution lines is complex, and there are many vegetation and obstacles around the lines. In this case, the UAV is easy to touch foreign objects by mistake during flight, resulting in aircraft explosion. Second, the volume of distribution equipment is much smaller than that of transmission equipment. In this case, it is very difficult for UAV to identify the defects of distribution equipment. The above characteristics of distribution lines and equipment put forward higher requirements for the performance of UAV front-end target tracking and environmental recognition. In order to reduce the risk of blowing up and hanging up in the process of distribution line UAV inspection and improve the efficiency of UAV inspection, this paper carried out the research on the front-end target tracking and intelligent recognition technology of distribution network UAV Based on deep learning. The research results have guiding significance for improving the applicability of UAV patrol technology in the field of power distribution.

Keywords: Distribution Network · Unmanned Aerial Vehicle · Target Tracking · Deep Learning

1 Introduction

Recently, UAV patrol technology is more and more widely used in the field of power distribution network. This new technology has greatly improved the patrol efficiency of the power distribution discipline [1]. However, the complex operating environment of distribution network and the small volume of distribution equipment put forward higher requirements for UAV target tracking technology [2].

H. Yang et al. (Eds.): SmartGIFT 2022, LNICST 483, pp. 513–518, 2023.
https://doi.org/10.1007/978-3-031-31733-0_44

This paper first analyzes the single target tracking process of UAV, and then further analyzes the twin network target tracking technology based on model compression in the complex operation environment of distribution network. The target tracking algorithm for the traditional twin network consumes a lot of computation, which can not be used on the UAV platform; And due to the small target of distribution equipment, it is necessary to make more efficient use of the characteristics of different layers. In this paper, the geometric median method is used to compress the feature extraction network RESNET to improve the operation efficiency of the model, so that the model can run on the UAV platform, and the tracking accuracy is controlled within an acceptable range. In view of the shortcomings of the twin network tracking algorithm siamrpn + + in multi-layer feature fusion, an improved depth feature fusion weighting method is proposed, and the convolution neural network is used for training the weights to make the algorithm more accurate for classification and regression results.

2 UAV Single Target Tracking Process

After decades of development, visual tracking technology has made great progress, and the execution steps of visual tracking methods have been studied thoroughly [3]. First, initialize the model parameters. That is, the current frame state of the image target to be tracked is taken as the initial state of future tracking. The second step is to analyze the characteristic parameters and establish the target model. The second step is to analyze the image feature parameters and establish a feature model. The third step is to apply the final target strategy to the image feature model of the previous step. In this way, a new image feature model can be obtained. Finally, repeat the above steps [4, 5]. Figure 1 is the basic flow chart.

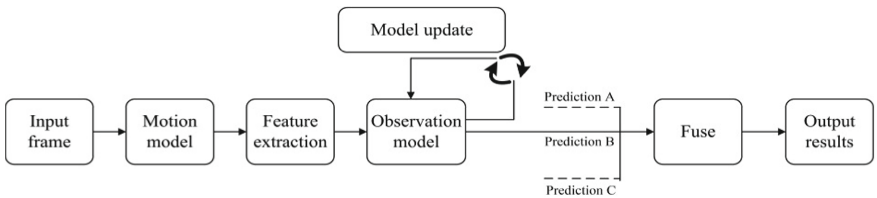

Fig. 1. Target tracking process

The target tracking strategy can adopt generation method. The first step is to learn the global information of the image and extract the feature parameters. The second step is to classify various characteristic parameters. The third step is to analyze the area close to the target features. The fourth step is to compare the template with similar areas. Finally, find the area with the highest similarity (Fig. 2).

In addition to the generation method, the target tracking strategy can also use the discriminant method. The discriminant method directly learns the target model through data samples. In target tracking, the discriminant method directly trains a model through sample distribution for tracking targets. The specific step is to give a series of samples, train a model through the sample data, and output the probability value. When there

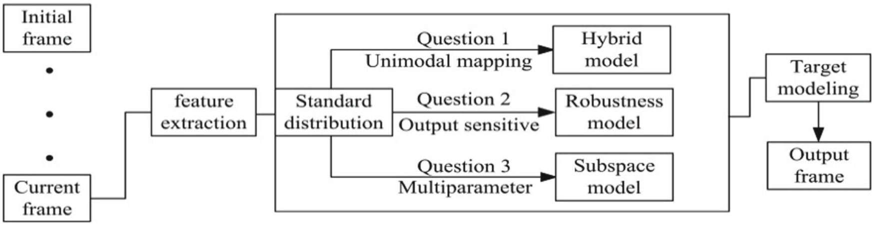

Fig. 2. Target tracking process

are new samples next time, the classification can be judged by the discriminant model. Therefore, the difference between the discriminant method and the generation method is that the discriminant method directly studies the prediction model and then predicts. After the initialization of the target, the feature is extracted and the model is established. The foreground target and the background are divided by the classifier. The tracker tracks the foreground target and updates the window until the next frame. At the same time, the background information is added in the next frame to increase the interference of the background, which improves the robustness of the classifier. The flow of discrimination class tracking method is shown in Fig. 3.

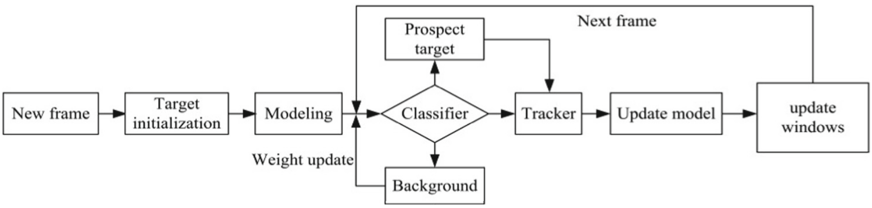

Fig. 3. Target tracking process

As shown in Fig. 4, the first step is to initialize the first frame. The second step is to use the initialized prediction target as the input signal of the second frame. The third step is to extract different visual features to better describe the input. The fourth step is to convolve and correlate the FFT converted signal with the correlation filter, where FFT is the fast Fourier transform. The fifth step is to invert the operation result of the fourth step to obtain the spatial confidence graph. The sixth step is to extract new feature parameters from the spatial confidence graph. The seventh step is to train the data processing strategy and update it with the expected output.

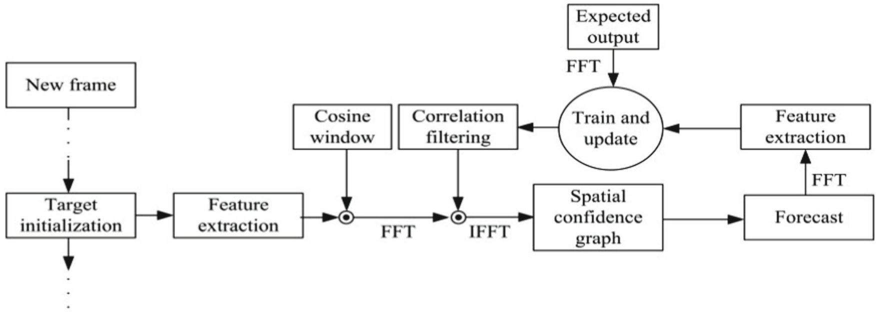

Fig. 4. Target tracking process

3 Twin Network Target Tracking Based on Model Compression

The siamrpn++ model used in this paper uses the residual network structure. Although the performance is very strong, this high computational cost is very expensive to deploy on UAV. A low computational cost deep convolution neural network can be obtained by model compression to optimize the model. One method of model compression is pruning. There are two main pruning methods. They are weight pruning method and filter pruning method.

The weight pruning method is to delete the weight values of related parameters, which leads to non institutional sparsity. This irregular structure is not hardware friendly. Instead, filter pruning directly discards the entire selected filter and leaves a model with a regular structure. This paper adopts filter pruning method to accelerate the residual network, improve computing efficiency, and reduce memory and power consumption. In this paper, the filter pruning strategy based on geometric median method fpgm selects the most replaceable filter for pruning. Specifically, we calculate the geometric median of the filter in the same layer. According to the characteristics of geometric median, the filter near it can be represented by residual filter. Therefore, pruning these filters will not have a substantial negative impact on the performance of the model. Fpgm is used to prune the most replaceable filter containing redundant information, so that it can still maintain good performance when the norm based criterion fails.

The twin network model siamrpn++ mainly solves the problem of how to apply deep networks such as RESNET and inception to the tracking network based on twin networks. After siamfc algorithm, although there have been many tracking algorithms based on twin networks, most of these networks use shallow networks as feature extractors. In previous attempts, directly using the pre trained deep network will lead to the decline of the accuracy of the tracking algorithm. Therefore, a key problem to be solved for the tracker based on twin network is how to use the deeper network for tracking. The relevant operations in siamfc can be regarded as calculating the similarity of each position in the form of sliding window, so it needs to have translation invariance, and the filling in the depth network will destroy this translation invariance, because according to the training method of siamfc, the positive samples are in the positive center, and the network will gradually learn this statistical characteristic, and learn the distribution of positive samples in the samples, that is, the central position is a positive sample, and the edge position is a negative sample, The filling method will change the original edge position to the center position, resulting in performance degradation. Therefore, when training, let the target not focus on the central position, but let it be in different positions of the image, offset a certain distance from the central point, so as to alleviate the problem of shallow network caused by unable to fill. Figure 5 is Siamrpn++ architecture.

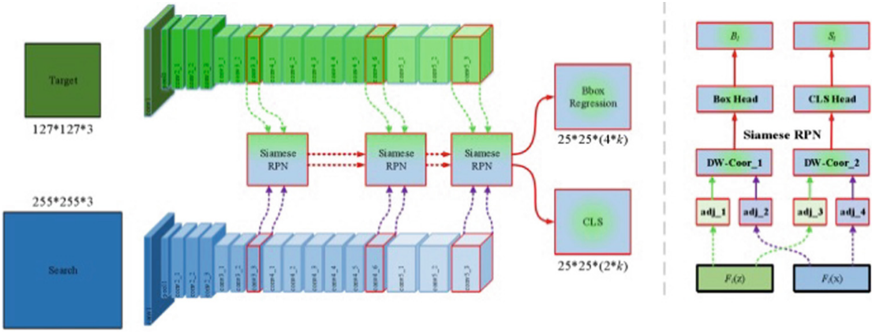

Fig. 5. Target tracking process

The output of multiple Siamese region suggestion blocks can be fused to improve the operation effect. The siamrpn block is shown on the right. Siamrpn++ uses resnet-50 as the backbone. Each block output is appended with a 1 × 1 to keep the number of characteristic image channels 256. By uniformly sampling and processing samples, the filling operation is added to the network characteristic graph, and the parameters of the filled characteristic graph will increase after convolution, which brings a certain amount of computational consumption. Siamrpn++ cuts the central area of the image as a template, and makes the target distributed in the image template. By reducing image pixels, the amount of calculation is reduced. Siamrpn++ also improves the cross-correlation layer in the previous twin network, uses the deep correlation layer to achieve more efficient information correlation, reduces the amount of parameters, increases the fine-tuning of resnet-50 backbone network, and improves the performance of the feature extractor. After adopting the new sampling strategy in the training process, RESNET can be successfully trained and the video can be tracked.

4 Conclusion

Aiming at the complex operating environment of distribution network and the small size of distribution equipment, this paper deeply analyzes the more applicable target tracking technology of UAV. The deep convolution neural network with low computational cost and high accuracy is obtained by model compression. At the same time, the depth feature fusion weighting method is improved, and the convolution neural network is used to train the weights, so as to obtain an efficient and high-precision target tracking method.

Acknowledgment. This research work is supported by State Grid Hunan Electric Power Company Limited. The number of the science and technology project is 5216A521001J.

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