Design of Porcelain Insulator Defect Recognition System Based on UAV Line Inspection Image

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Abstract. With the progress of technology and the improvement of equipment quality, the coverage of China's transmission network is expanding rapidly. Large power grids across complex and volatile terrain and dangerous high-voltage transmission lines are also being extended. Therefore, the traditional method of checking the circuit manually is no longer feasible due to its low efficiency, low precision, high risk and high cost. However, unmanned aerial vehicles (uavs) are a perfect way to circumvent these problems by inspecting transmission lines instead of workers. This paper takes the application of unmanned aerial vehicle in power line patrol as the research background, takes the porcelain vase in power transmission as an example, and realizes the image recognition and damage judgment system of the porcelain vase with specific target. Based on the image processing technology of machine learning and MATLAB, the target detection method of YOLO v3, the semantic segmentation method of Deeplab v3+, and the improved damage analysis method of ellipse fitting were respectively used to make the damage judgment and analysis of porcelain vats based on the intelligent image recognition interception, contour extraction and semantic segmentation. In the actual site of 166 porcelain bottles damage detection, damage detection accuracy reached 86.7%. Finally, the identification system of porcelain vase defect is realized.

Keywords: UAV · Image processing · Semantic segmentation

1 Introduction

1.1 Research Status

UAV technology includes image processing, electronic technology, flight technology, and automatic control. In the UAV power inspection circuit, image processing is a necessary step for the system to finally obtain intuitive results [1].

Since 2014, the State Grid Corporation of China has successively convened ten pilot units, established drone inspection bases in Shandong and Wuhan, and established a professional drone training college for power systems in Laiwu City, Shandong Province.

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Provide talents for the development of mechanical and electrical inspections. At the same time, power companies in various regions have established a special drone system and a complete drone inspection business process. At the same time, the State Grid Chongqing Electric Power Company has realized the establishment of a three-dimensional model of the transmission line, and has made phased progress in the visualization of the inspection system. The State Grid Zhejiang Power Transmission and Transformation Company realized the construction of high tower lines in January 2019. Among them, the tower is 380 m high and uses drone traction and unwinding technology. The application of this technology can greatly reduce costs and operational risks., While effectively improving work efficiency. The success of this project is of great significance for UAV power line inspection [2, 3].

At present, according to the latest data released by the State Grid Corporation of China, the efficiency of UAV line inspection is 8 to 10 times that of manual line inspection. In the current power line inspection work, UAV power line inspection is in actual production. The application in life has also reached 1/2. It is not difficult to see that in the near future, UAV power line inspection will become the most important and most widely used inspection method for power grid units [4].

In 2000, an unmanned aerial vehicle for transmission line inspections was developed by scholars at the University of Wales in the United Kingdom. Electric energy can be extracted automatically from the running line, and the distance to the inspection line is very close, so there will be no problem of crossing with other waterways. The design scheme has passed the feasibility verification.

Japan's current research on the application of UAV line inspection systems to transmission lines is relatively mature. The system can already realize automatic fault detection, three-dimensional image monitoring, and automatic detection of lightning flashover points, the inclination of towers, the rust of iron tower materials, and whether cement poles are automatically detected. There are major defects such as cracks.

Australia's GSIRO Research Institute has completed the design of a fully automated line patrol UAV. Due to its advantages such as long endurance, stable flight status, high definition of collected images, and good detection effect, it is currently at the forefront of research on UAV line patrol.

Based on GPS positioning and computer vision analysis, Mejias and others of the Polytechnic University of Madrid, Spain, focused on the design of the navigation system in the process of UAV patrol. They have made innovative progress in UAV navigation and target positioning, and added automatic Obstacle avoidance function, this research has made breakthroughs in improving the accuracy of fault detection and the safety of UAV flight and landing [5].

In general, the research on UAV inspection systems in developed countries has not only completed the hardware part, but most of them have been paying attention to the later image and video processing, and a few have begun to use higher-end Lidar UAV applications [6–8].

1.2 The Research Method and Content of This Article

This article takes porcelain bottles as an example, aiming at the images taken by the UAV during the line inspection process, aiming to realize that the system can automatically and intelligently identify whether the electrical equipment is intact without manual intervention. Thereby reducing the workload of line inspection and manual screening of images in the later stage, which has certain practical value corresponding to the actual production.

Based on the YOLO v3 model and Deeplab v3+ model, this design intelligently recognizes and intercepts the exterior porcelain bottle images taken by the drone, and performs semantic segmentation on the intercepted independent images. Finally, the algorithm is used to determine whether the porcelain bottle is damaged according to the contour of the porcelain bottle. And carried on the simulation test to the above content.

2 Target Detection Part

2.1 YOLO Overview

In recent years, machine learning algorithms have developed rapidly. Among many image processing technologies, machine learning-based image processing technologies are increasingly becoming mainstream. In this design, a target detection technology based on the YOLO (You Only Look Once) algorithm is used.

YOLO is the abbreviation of You Only Look Once proposed by Redmon and Diccala, and is currently and updated to the third generation. The model algorithm is based on the deep neural network, and finally realizes the identification and positioning of the target. Its advantage lies in the extremely high efficiency, so it can be used in projects with high real-time requirements [10–12].

The fast detection speed of YOLO (You Only Look Once) is attributable to its use of regression to analog target detection. In order to achieve end-to-end recognition, YOLO directly predicts the parameters of the box surrounding the target in the original image. Compared with early algorithms such as edge detection algorithm and directional gradient histogram algorithm, it has the advantages of high accuracy and stronger robustness [13].

2.2 The Structure and Algorithm of YOLO

YOLO merges the candidate areas, so the overall structure presents a five-layer structure of first input layer, then 24 convolutional layers, then pooling layer, and finally 2 fully connected layers and output layer, as shown in Fig. 1. By improving R-CNN, YOLO extracts image features by using a convolutional neural network that is more suitable for target detection, and then improves the use of fully connected layers to detect target positions and types, thereby greatly improving the running speed and detection accuracy [14].

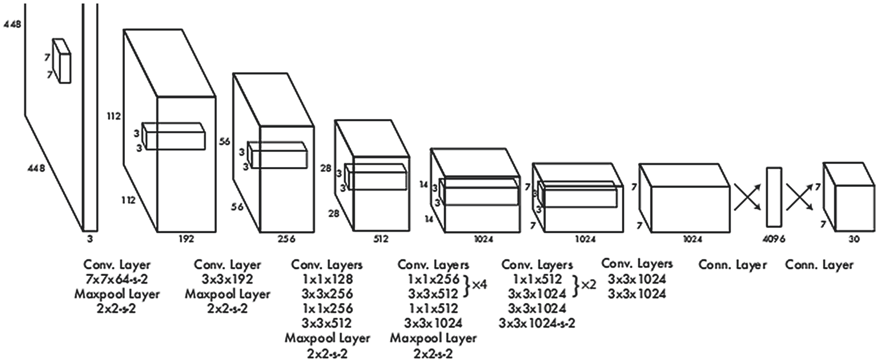

Fig. 1. The structure of the YOLO

As shown in Fig. 1, the leftmost is the input layer of YOLO, as the entrance to the entire network, it is responsible for image preprocessing, which corresponds to the process of generating feature maps in the convolutional neural network. The input layer of YOLO has no requirements for the number of input image pixels. Through the normalization of the original image, proportional cropping, image enhancement and other processing, as well as the decomposition of the RGB (red, yellow and blue) three channels in the color image. Superimposed, the output of YOLO's input layer is an image with a fixed pixel size of 448 * 448 * 3 in each dimension. On the right side of the input layer are 24 convolutional layers. Their function is to convolve the result feature map produced in the previous step. Through a series of convolutions and operations, the feature information in the feature map is refined. This information will be used for subsequent target detection, positioning and classification [14].

2.3 Improvements in YOLO V3

The main idea of the YOLOv3 algorithm is to absorb the advantages of the major algorithms, and to further improve efficiency while maintaining the performance of the previous version. In addition, the YOLO v3 version has made innovative adjustments to the detection of small targets and achieved significant results. Effectiveness. Among them, the most exciting improvement is embodied in the proposal of Darknet-53 backbone network and multi-scale feature detection.

The basic network structure of YOLO v3, which contains many 1 * 1 * 3 * 3 size convolution operations, which are mainly used to extract image features. After each convolution, there is a normalization operation and an activation operation of Leaky RELU. A 1 * 1 layer and a 3 * 3 layer are superimposed together as a frame, and the produced frame is superimposed with the frame of the previous layer to produce a frame difference. Then increase the speed (step size) of the convolution kernel to downsample the image. In addition, YOLO v3 replaces the fully connected layer in the previous version of the neural network with a 1 * 1 * 3 * 3 convolutional layer, and outputs the results in three different sizes of feature layers [15–17].

2.4 YOLO V3 Algorithm Target Detection

Environment Configuration
Darknet is an open source code. After downloading from the official website, install it according to the specific situation of the computer.

Production of Data Set
Use labeling to select the target, and the resulting labeled image is shown in Fig. 2. And use the VOC2007 format as a template to make a data set.

Fig. 2. The production of VOC data set

Model Training
Use the prepared data set to train the YOLOv3 model in Darknet until a certain weight file is output.

Model Test
Use drone aerial images to test the trained data set, and the model test result after training is shown in Fig. 3.

Fig. 3. YOLO v3 model target detection results

3 Semantic Segmentation Module Based on Deeplab Algorithm

3.1 Introduction of the Deeplab Model

DeepLab is a semantic segmentation method with the main idea structure including deep convolutional neural networks (DCNNs) and fully connected conditional random field models (DenseCRFs).

It organically combines the outermost layer of the deep convolutional neural network with the conditional random domain, mainly absorbs the hole convolution algorithm, broadens the receptive field to obtain the image information of the farther area of the edge of the marked object contour, so as to realize the improvement of the neural network. The positioning accuracy is as high as 71.6% in the semantic image segmentation task of the Pascal voc dataset in 2012. And faster running speed can be obtained on GPU [18].

3.2 Optimization History of Deeplab

The Deeplab series has now been updated to the v3+ version, and the entire series shows a trend of continuous optimization. For the Deeplab v2 version, there are two main improvements compared to the previous version. One is that the VGG16 embodied in

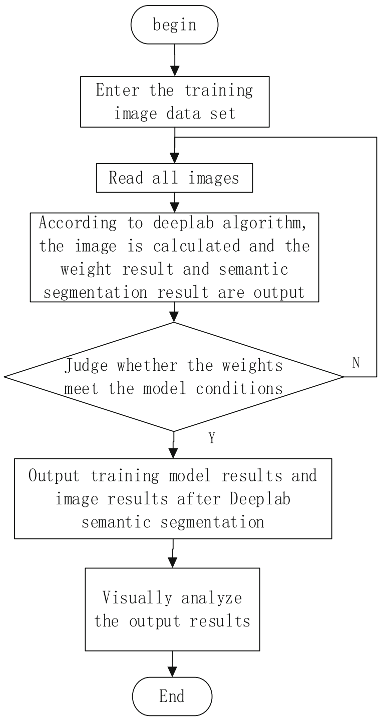

Fig. 4. The semantic segmentation part structure

the base layer is used in the v3+ version. It is ResNet, which obtains more accurate segmentation results than the previous version. The second is to add "porous spatial pyramid pooling", thereby increasing the multi-scale nature of segmentation.

Deeplab v3+ version adds the decoder part on the basis of Deeplab v3 version. Specifically, the entire process of the v3 version is used as an encoder in the v3+ version structure, and a part of it is added as a Deeplab v3+ version of the decoder at the back end. Therefore, the v3+ version presents a new encoder-decoder structure as a whole.The semantic segmentation part is shown in Fig. 4 [25–27].

Next, the semantically segmented data set was made as shown in Fig. 5

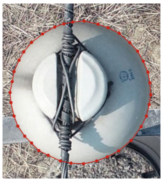

Fig. 5. Production of semantically segmented data sets

The Deeplab v3+ version uses dilated convolution to control and adjust the resolution extracted by the decoder, thereby improving the operating efficiency while maintaining the accuracy of the results. The semantic segmentation results of the target contour of the deeplab model is shown as Fig. 6.

Fig. 6. Semantic segmentation results of the target contour of the deeplab model

4 Ceramic Vase Contour Damage Identification Module

4.1 Edge Detection

Edge detection is to extract the transform discontinuous part from the original image, that is, the image edge. Boundary information is hidden in the edge of an image. Edge detection provides a basis for further image processing and analysis using this information. At the same time, because edge detection can weaken a lot of useless information and noise in the image at the same time can retain the basic object characteristics. It also has the function of reducing workload and improving efficiency [28–30].

4.2 Canny Operator

The Canny operator organically combines the first derivative with the Gaussian function, and adds optimization ideas. The Canny operator advocates three principles: low error rate, high positioning accuracy, and unilateral response. Using the symmetry and variable separability of the two-dimensional Gaussian function effectively improves the accuracy of edge detection [31, 32].

Canny's edge detection operator is relatively complete and robust, with high accuracy of detection results, and can automatically eliminate false edges. But its disadvantage is that the amount of calculation is large and the adaptability is poor, that is, the output picture is not clear [33].

4.3 Fitting the Contours of Porcelain Vases

As shown in Fig. 7, in the image of the porcelain bottle taken by the drone, the image on the left is the image of the complete porcelain bottle, and the image on the right is the image of the damaged porcelain bottle, and their respective contours are shown in Fig. 8. The contour of the porcelain bottle image processed by deeplab is very obvious, so the accuracy of the edge detection operator is not high. In view of the smooth curve fitting in the next step, the design selects the canny operator for edge extraction.

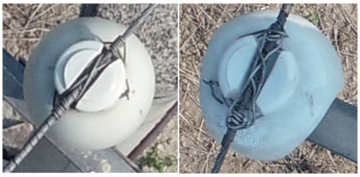

Fig. 7. Image comparison of intact and damaged porcelain bottles

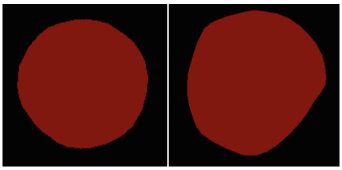

Fig. 8. Comparison of the contours of complete and damaged porcelain bottles

It can be seen that the outline of the upside down image of the complete porcelain bottle is close to a perfect circle, while the upside down image of the damaged porcelain bottle is an irregular figure.

Due to exposure to the wild, the damage of porcelain bottles is mostly out of control. In practice, we found that the damage of the porcelain bottle will appear to be close to an oval after damage as shown in Fig. 9.

Fig. 9. Approximately oval porcelain bottle image after damage

After fitting it to an ordinary ellipse, the result is shown in Fig. 10.

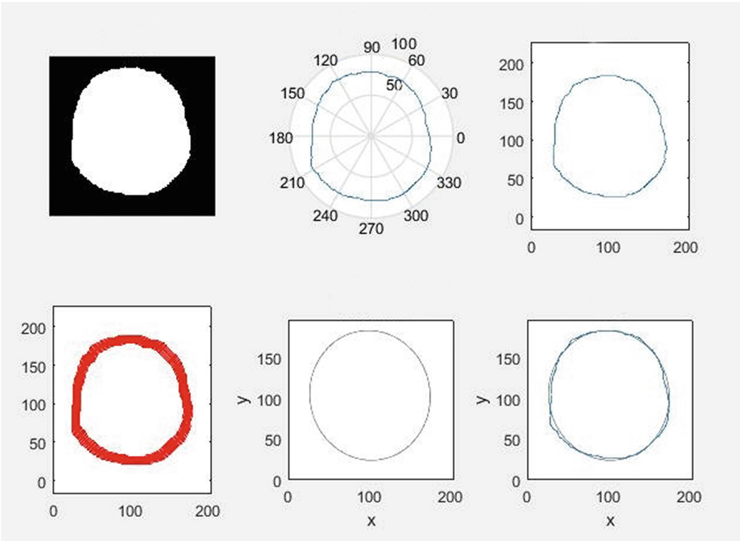

Fig. 10. Ellipse fitting to approximate the contour of an elliptical porcelain bottle after damage

The contour of the damaged porcelain bottle is very similar to the contour after the ordinary ellipse fitting, so ordinary ellipse fitting cannot be used. The method used in this article is to simulate and restore the state before the damage. Assuming that the contour edge before the damage is a standard ellipse, calculate the difference between before and after the damage Error to get a quantified damage index.

The algorithm steps are as follows:

(1) Binarize the output result of the semantic segmentation of the Deeplab v2 model into a grayscale image with only two colors of black and white.
(2) Using the edge detection algorithm, this paper uses the sobel operator for edge extraction to obtain the single-line image of the contour of the porcelain bottle.
(3) Set up the ellipse equation, fit the contour to the ellipse, and find its geometric center.

(4) Declare the identification variables. If the fitted ellipse contour has an intersection with the actual contour, the ellipse contour will be enlarged to 1.01 times the original ellipse until the circumscribed ellipse of the actual contour of the porcelain bottle is approximated.
(5) Use the improved standard deviation algorithm to calculate the fitting error between the contour of the external ellipse and the contour of the original porcelain bottle.
(6) Draw up the threshold through a large amount of data statistics.

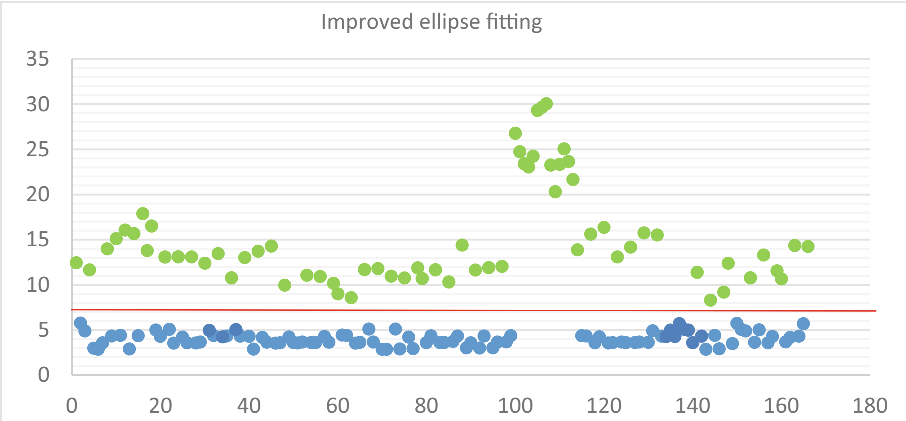

Fig. 11. Experimental results are fitted with improved ellipse

The algorithm can approximate the minimum envelope fitting ellipse of the vase contour. Through subsequent quantitative fitting errors and experiments on the existing data set (166 porcelain bottle images taken by UAVs), the results are shown in Fig. 11. As you can see, the available data are within reasonable bounds.

5 Conclusion

In this paper, a damage detection method based on YOLO_v3 and Deeplab_v3+ machine learning models is designed. Considering the randomness of the shape of damaged porcelain bottles, the existing ellipse fitting algorithm is improved to realize whether the porcelain bottles are damaged. In the experimental data, the experimental accuracy is 100%, and in the actual production, the accuracy is 86.7%. This paper puts forward a solution to the difficult problem of long-distance transmission equipment detection, which is of practical significance to production practice.

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