Detection of Insulator Defects Based on YOLO V3

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Abstract. The power system of China is still composed of power generation, transmission, substation, power distribution and other links. To ensure the safety and stability of transmission lines is an important part of large-scale transmission process, and the insulators are important in the transmission line. The existing parts, such as surface contamination, cracks, damage and other surface defects seriously threaten the operation safety of the power grid. Faults caused by insulator defects are currently the highest proportion of power system faults, so the surface defects of insulators are detected and timely completion of fault repair becomes more important. In this regard, this paper proposes a target detection algorithm based on YOLO V3 (You Only Look Once: Real-Time Object Detection), which utilizes the powerful learning ability of deep convolutional neural networks and a large number of data annotation samples. The image of the insulator photo-graphed by the machine is detected and classified, finally the intelligent detection of the intact insulator and the defective insulator is realized. The experimental results show that the YOLO V3 based insulator defect detection method can effectively identify the defective insulator strings from the aerial image of the drone. Compared with the previous insulator defect identification method, the accuracy and detection time are significantly improved, and it can realize the intelligent detection of intact insulators and defective insulators.

Keywords: Insulator · YOLO V3 · Target detection · Defect detection · Target classification

1 Introduction

The invention and widespread use of electricity have brought convenience to human beings. Electrical equipment such as computers, mobile phones, and smart appliances have made us more dependent on electricity, which has become a necessity in people's life [1]. At present, the transmission lines most commonly used are overhead transmission lines, which are mainly composed of wires, overhead ground wires, insulator strings, poles, grounding devices, etc. The insulator is a large number of components in

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the transmission lines, playing the role of electrical insulation and mechanical support, and is also a fault multiple component. Therefore, it is necessary to carry out regular inspection on the transmission lines and timely replace and maintain the insulators that have failed or are about to fail.

At present, the physical methods for on-line detection mainly include the following methods: observation method, ultraviolet imaging method and infrared imaging method, laser Doppler vibration method, ultrasonic flaw detection method, etc. [2]. The above have played a certain role, but mainly rely on manual monitoring, artificial vision consumes a lot of manpower and material resources, low efficiency, but also due to differences in personnel experience and personal qualities, the detection effect is difficult to standardize [3].

Along with the continuous advancement of technology, there has been a transmission line inspection platform based on a helicopter and unmanned aerial vehicle. The inspection platform is characterized by high efficiency, accuracy and safety, has become the main method of transmission line inspection in recent years. In order to understand the operation of and the potential hidden dangers of the transmission line, the power department used the drone inspection instead of the manual inspection [4, 5], by loading the camera on the platform to obtain a large number of aerial images, including effective insulator targets. If only by manpower for visual judgment without automatic image analysis, it is easy to cause missed or misjudged phenomenon, resulting in major safety hazards in transmission lines [6].

At present, there are related researches on the detection methods of insulators. The commonly used detection methods include: Aerial image detection method based on skeleton extraction [6]; Insulator string automatic state recognition based on infrared image [7]; Color matrix based Insulator single-chip infrared image fault diagnosis [8]; In literature [9] proposed a method for detecting internal defects of composite insulators based on misaligned speckle interference. It is used to eliminate the unqualified insulators in production and the concealed defects of composite insulators in diagnostic operation. These methods require manual feature extraction, with a heavy workload and a low recognition rate, which is likely to lead to the misdetection or omission of insulators due to the loss of subjective information [10]. In response to this phenomenon, researchers have proposed an image segmentation method based on deep learning [11, 12]. Literature [8] uses infrared imaging technology to acquire imaging, and the process of image treatment is as follow: image segmentation, data regularization, homomorphic filtering and data randomization, and BP neural network algorithm (The back propagation neural network algorithm is a multi-layer feed forward network trained according to error back propagation algorithm and is one of the most widely applied neural network models. BP network can be used to learn and store a great deal of mapping relations of input-output model, and no need to disclose in advance the mathematical equation that describes these mapping relations. Its learning rule is to adopt the steepest descent method in which the back propagation is used to regulate the weight value and threshold value of the network to achieve the minimum error sum of square) to extract insulator single-chip center. The RGB (The RGB color model is an additive color model in which red, green, and blue light are added together in various ways to reproduce a broad array of colors. The name of the model comes from the initials of the three additive primary colors, red, green, and blue) color matrix of the line is trained and analyzed as characteristic parameters, and an infrared diagnostic model of the insulator single chip based on the center line color matrix in the fault condition is constructed. In the literature [13], the six-rotor electric drone was introduced, and the manual inspection and the drone inspection were combined. Based on the threshold segmentation, morphology and edge detection techniques, the connected domain characteristics and shape characteristics of the insulator were designed. It can adapt to the complex background of aerial photography and multi-angle insulator self-explosion defect recognition algorithm to realize automatic detection of insulator defects and reduce manual intervention. For example, power inspection insulator detection based on convolutional neural network; it can automatically be compared with traditional detection methods. Compared with the traditional algorithm, improve the recognition accuracy under the complex background. However, in the case of image classification of insulators by convolutional neural network, an image classification block is required for each pixel. For insulator images with complex background, the classification block of adjacent pixels has high similarity which leads to slow and accurate network training [10]. Aiming at this problem, this paper based on the defect detection method of insulator in YOLO V3, using the powerful YOLO V3 real-time target detection algorithm, an end-to-end insulator defect detection method based on deep learning detection algorithm is proposed. Insulators are detected and automatically distinguish between defective insulators and intact insulators. Therefore, the automatic identification of insulator faults has practical significance for the inspection of transmission lines. Since most of the methods for detecting insulator defects based on aerial photographs are carried out in the laboratory environment, which has great limitations and does not take into account the complex background images of insulators and other factors, it is very important to use the YOLO V3 algorithm to study the automatic detection method for insulator surface defects.

The organization of the paper is as follows. In Sect. 2, the advantages of YOLO V1 and YOLO V2 relative to other target detection algorithms are summarized. In Sect. 3, the main algorithm part of YOLO V3 is introduced: basic method and network model design. In Sect. 4, a brief analysis of the experimental results and data. In Sect. 5 presents the conclusions.

2 Related Work

In this section, we review the advantages of YOLO V1 [14] and YOLO V2 [15] relative to other target detection algorithms, and give a brief overview of their advantages. The most important point is to point out that YOLO V3 is relatively inspecting small objects in relation to V1. And V2 speed and accuracy improvements. Object detection systems before YOLO (You Only Look Once: Unified, Real-Time Object Detection and YOLO9000: Better, Faster, Stronger) used classifiers to perform physical detection tasks, The method is to use a classifier to evaluate the presence or absence of the object on the boundary boxes of different positions and sizes of a test graph. For example, in the DPM system (Deformable Part Model System), a sliding window is used to evenly slide the whole image, and a classifier is used to evaluate whether there is an object. Other methods proposed after DPM, such as the R-CNN

(Region-Convolutional Neural Networks) method, use region proposal to generate possible bounding boxes of the entire image that may contain objects to be detected. And then use classifiers to evaluate the meshes, improve the bounding boxes by preprocessing, eliminate duplicate detection targets, and re-predict the grid based on other objects in the entire scene. The entire process is slow to execute, and because these links are trained separately, detection performance is difficult to optimize. Unlike these object detection methods, YOLO treats the object detection task as a regression problem, using a neural network to directly predict the coordinates of the boundary box, the confidence of the object contained in the target grid and the probability of the object from a whole image. YOLO's object detection process is done in a neural network, so end-to-end optimization of object detection performance is achieved, while YOLO detection of objects is extremely fast, the standard version of YOLO can reach 45 frames per second on Titan X GPU (A graphics processing unit, also occasionally called visual processing unit, is a specialized electronic circuit designed to rapidly manipulate and alter memory to accelerate the creation of images in a frame buffer intended for output to a display). The smaller version of the network Fast YOLO can maintain a detection speed of 155 frames per second while keeping the mAP (Mean Average Precision is the standard single-number measure for comparing search algorithms) twice as fast as other real-time object detectors. However, since the YOLO V1 training model only supports input of the same resolution image as the training image, and the target detection effect is relatively poor for relatively small targets, YOLO V2 provides power. YOLO V2 solves the problem that V1 can only input fixed size. The problem, but still not good at detecting small objects, is easy to produce object positioning errors, especially for dense objects. So this article uses YOLO V3 as the insulator defect detection algorithm.

3 Defect Detection of Insulator Based on YOLO V3

In the traditional power transmission line insulator target detection task can be divided into two aspects. First check for the target. That is, the target of the insulator is positioned in the image, where in the unfavorable factors such as complex background and image resolution are overcome. The insulators classified as intact insulators and defective insulators are classified according to the state characteristics of the insulators. Extracting features that adequately identify defective insulators is currently the most critical.

3.1 Basic Methods

Firstly, the feature extraction network is used to extract the features of insulator image, and a feature map of a certain size is obtained. For example, see (Fig. 2), the input insulator image is divided into S * S grids. The grid is responsible for detecting the insulator in which grid the center coordinates of the insulator fall. Since a fixed number of bounding boxes are predicted in each grid, the bounding box with the highest confidence value of the bounding box and the real insulator is selected and Ground Truth is the union of them, which is the IOU (Intersection over Union is an evaluation metric used to measure the accuracy of an object detector on a particular dataset. We often see this evaluation metric used in object detection challenges). The optimal situation is that IOU = 1 (that is, the predicted bounding box completely coincides with the bounding box of the real insulator) (Fig. 1).

$$IOU = \frac{D\text{ectionResult} \cap G\text{round}T\text{ruth}}{D\text{ectionResult} \cup G\text{round}T\text{ruth}} \tag{1}$$

The neural network predicts the bounding box by 4 coordinates: t_x, t_y, t_w, t_h. t_x, t_y represents the central coordinate of the predicted bounding box; t_w, t_h represents the width and height of the predicted bounding box, if the cell deviates from the upper left of the insulator image by (c_x, c_y), and the bounding box prior has width and height p_w, p_h, then the final grid predictions value correspond to

$$\begin{aligned} b_x &= \sigma(t_x) + cx \\ b_y &= \sigma(t_y) + cy \\ b_w &= p_w e^{tw} \\ b_h &= p_h e^{th} \end{aligned} \tag{2}$$

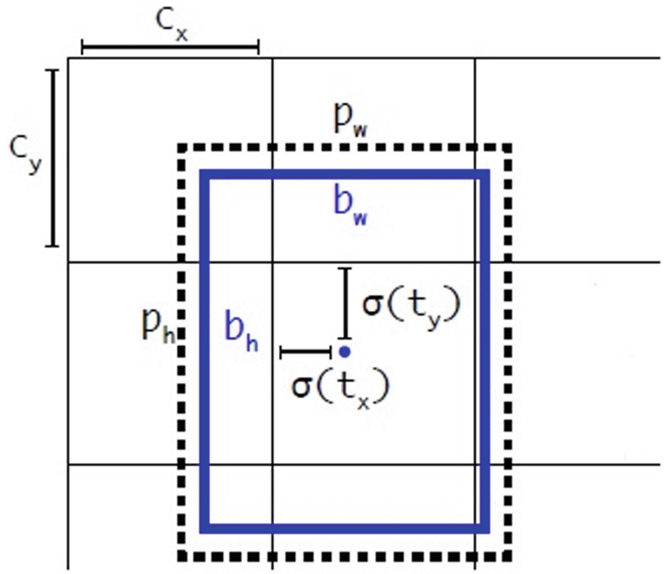

Fig. 1. Bounding boxes with dimension priors and location prediction.

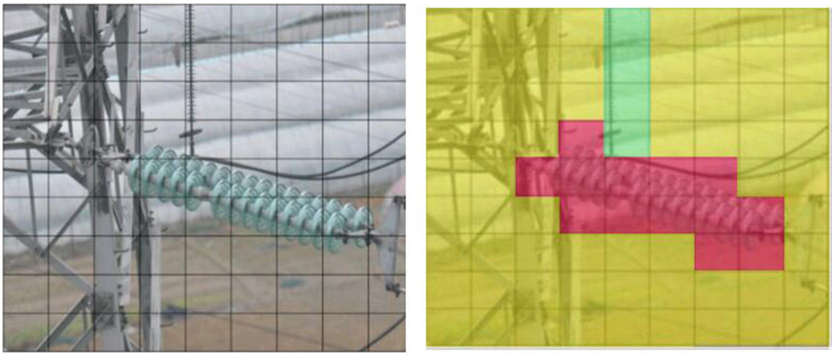

Fig. 2. Model schematic (Color figure online)

While predicting the bounding box, each grid also needs to predict the probability of three conditional categories, that is, the probability that each grid belongs to the background, the complete insulator, and the missing insulator. When an insulator is included in a mesh, it belongs to a complete insulator or missing insulator should be maximized. When the mesh does not contain an insulator, belong to the background should be the greatest. See (Fig. 2, the light red grid belongs to the missing insulator, the light green grid belongs to the complete insulator, and the yellow grid indicates the predicted background. To enhance the accuracy of the detection of small insulators, YOLO V3 uses an FPN (Feature Pyramid Networks for Object Detection. A top-down architecture with lateral connections is developed for building high-level semantic feature maps at all scales) upsampling and fusion approach.

3.2 Network Model

The whole network adopts Darknet-53. On the one hand, it adopts full convolution. On the other hand, it introduces a newfangled residual network stuff. Profit from the Residual structure of ResNet (Residual Neural Network). The model has improved its accuracy significantly. Darknet-53 is only a feature extraction layer. In the implementation process, only the convolution layer in front of the pooling layer is used to extract features, so multi-dimensional feature fusion and prediction branches are not reflected in the network.

YOLO V3 is a hybrid model that uses YOLO V2, Darknet-19, and Reset. It uses successive 3 * 3 and 1 * 1 convolutional layers during training, adding some shortcuts later. The connection structure predicts the position of the insulator in the image and the class probability prediction value of the defect based on the image features of the features extracted by the convolutional layer. Network Structure (Fig. 3). (From You Only Look Once: An Incremental Improvement).

	Type	Filters	Size	Output
	Convolutional	32	3 × 3	256 × 256
	Convolutional	64	3 × 3 / 2	128 × 128
1×	Convolutional	32	1 × 1	
	Convolutional	64	3 × 3	
	Residual			128 × 128
	Convolutional	128	3 × 3 / 2	64 × 64
2×	Convolutional	64	1 × 1	
	Convolutional	128	3 × 3	
	Residual			64 × 64
	Convolutional	256	3 × 3 / 2	32 × 32
8×	Convolutional	128	1 × 1	
	Convolutional	256	3 × 3	
	Residual			32 × 32
	Convolutional	512	3 × 3 / 2	16 × 16
8×	Convolutional	256	1 × 1	
	Convolutional	512	3 × 3	
	Residual			16 × 16
	Convolutional	1024	3 × 3 / 2	8 × 8
4×	Convolutional	512	1 × 1	
	Convolutional	1024	3 × 3	
	Residual			8 × 8
	Avgpool		Global	
	Connected		1000	
	Softmax			

Fig. 3. Darknet-53

3.3 How It Works

Prior detection systems repurpose classifiers or localizers to perform detection. They apply the model to an image at multiple locations and scales. High scoring regions of the image are considered detections. YOLO V3 uses totally different approach, which apply a Darknet-53 network to the entire insulator image. The network divides the image into different regions and predicts bounding boxes and probabilities for each region.

4 Experimental Results and Analysis

4.1 Dataset

In the process of deep neural network learning, we usually need a large amount of tagged data to train the model. Through the BP (Back Propagation) algorithm, the model learns better parameters to fit the mapping from input to output [7]. Therefore, we used a hand-labeled image of approximately 1,400 drones to train the model.

4.2 Experimental Results

The experimental test results are shown in (Fig. 4), and the box shows the defective insulator. The results show that the insulator defect detection algorithm based on YOLO V3 can quickly and accurately detect defective insulators in aerial photographs. Although it can't guarantee 100%, it solves the problem of correct distinction between intact insulators and defective insulators to some extent.

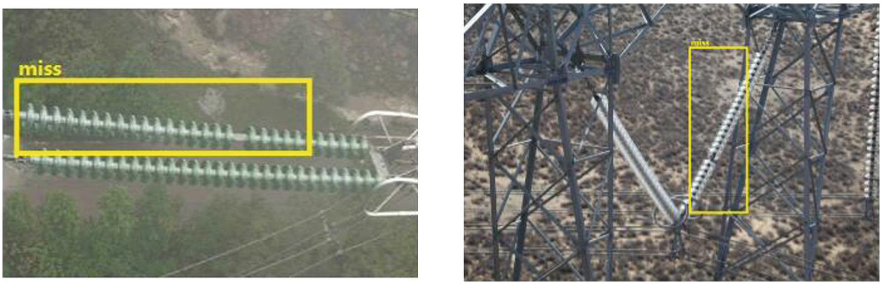

Fig. 4. Test results

In this paper, only more than 100 aerial insulator images are used for testing. The results are shown in Table 1. The average image of each insulator is only 0.55 s, which is faster, because there are fewer aerial images and some parts during the training. The insulators in the photo are the same, resulting in insufficient generalization.

Table 1. Insulator detection statistics

	Total	Positive identification	Error identification
Perfect insulator	118	112	6
Miss insulator	30	29	1

5 Conclusion

In the circuit inspection process, the accuracy and time of insulator defect detection are related to the safety of the entire transmission lines. This paper proposes an insulator defect detection algorithm based on YOLO V3 for the insulator photo taken by the drone, which can accurately detect the position of the defective insulator. For the insulator image of the complex background, the influence of the occlusion can be effectively eliminated. The missed detection rate and the false detection rate are greatly reduced. The higher accuracy rate can effectively reducing the insulation fault and safety issues, but due to the complex natural background of aerial insulators, all the training sets in this paper are limited, resulting in insufficient generalization features, but can meet the basic engineering application requirements. Next, we continue to collect images of composite insulator strings in various backgrounds. Propose more accurate defect detection algorithms as future research hotspots, providing new concepts and technical means for the detection of defective insulators in smart grids in China.

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References

1. Wang, L.J.: Research on insulator fault detection algorithm based on deep convolutional neural network. Tianjin University of Technology (2018)
2. Wang, J., Jiao, X.X.: Common faults and troubleshooting methods of insulator. Electr. Drive Autom. **36**(06), 50–53 (2014)
3. Li, L.X.: The UAV intelligent inspection of transmission lines. In: Proceedings of 2015 International Conference on Advances in Mechanical Engineering and Industrial Informatics (AMEII 2015), p. 4. Computer Science and Electronic Technology International Society (2015)
4. Li, X., et al.: Application and demand analysis of UAV in power industry. Electr. Appl. **34**(S2), 773–775 (2015)
5. Peng, X.Y., Liu, Z.J., Mai, X.M., Luo, Z.B., Wang, K., Xie, X.W.: A transmission line inspection system based on remote sensing: system and its key technologies. Remote Sens. Inform. **30**(01), 51–57 (2015)
6. Zhai, Y.J., Wang, D., Wu, Y., Cheng, H.Y.: Two-stage recognition method of aerial insulator images based on skeleton extraction. J. North China Electr. Power Univ. **42**(03), 105–110 (2015)
7. Yao, J.G., et al.: Algorithm research of automatically extracting the area of insulator from infrared image and state identification. J. Hunan Univ. (Nat. Sci.) **42**(02), 74–80 (2015)
8. Fu, W.P., Shi, F.X., Wang, W., Liu, Y.P., Ji, X.X., Pei, S.T.: Single insulator fault diagnosis method based on color matrix. Insul. Surge Arresters **285**(05), 226–232+240 (2018)
9. Liu, L.S., Wang, L.M., Mei, H.W., Guo, C.J.: Defects detection method for composite insulator based on shearing speckle interferometry. In: Proceedings of the CSEE, pp. 1–8 (2019)
10. Chen, J.W., Zhou, X., Zhang, R., Zhang, D.: Aerial insulator detection based on U-net network. J. Shaanxi Univ. Sci. Technol. **36**(04), 153–157 (2018)
11. Silver, D., Huang, A., Maddison, C.J., et al.: Mastering the game of Go with deep neural networks and tree search. Nature **529**(7587), 484–489 (2016)
12. Murthy, V.S., Gupta, S., Mohanta, D.K.: Digital image processing approach using combined wavelet hidden markov model for well-being analysis of insulators. IET Image Process. **5**(2), 171–183 (2011)
13. Wang, M., Du, Y., Zhang, Z.R.: Study on power transmission lines inspection using unmanned aerial vehicle and image recognition of insulator defect. J. Eelectron. Meas. Instrum. **29**(12), 1862–1869 (2015)
14. You Only Look Once: Unified, Real-Time Object Detection. http://pjreddie.com/yolo/. Accessed 09 May 2016
15. YOLO9000: Better, Faster, Stronger. http://pjreddie.com/yolo/. Accessed 25 Dec 2016