An Improved Object Detection Method for Automatic Electrical Equipment Defect Detection

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Abstract. Employing computer vision and machine learning on equipment defect detection has become an important trend of electric power inspection. This paper presents a new electrical equipment default detection method based on improved YOLOv3. By combining abundant geometric measures, Complete IOU (CIOU) make the bounding box regression during NMS more accurate. Focal loss function, which focus on differentiate between easy and hard examples, is employed to deal with the class imbalance problem. Experiment results show that the proposed approach obtains competitive performance compared with state-of-the-art deep learning object detection methods.

1 Introduction

With the development of computer vision and machine learning technology, Automatic electrical equipment defect detection has been more and more popular during electric power inspection. After captured by robot and video cameras, images of electric equipment are sent into object detection system to determine the class and location of defect. Such process avoids human inspection of images recordings, considerably accelerating the electric equipment inspection.

For several years, there have been many automatic electrical equipment defect detection techniques proposed. These methods can be divided into unsupervised or supervised manners. On one hand, the unsupervised methods search for robust appearance features for differentiating the normal equipment and defect ones. Prasad et al. [1] employed LBP-HF features to describe the texture appearance of substation equipment. Liu et al. [2] extracted texture features using a Gabor transformation. On the other hand, inspired by the good performance of machine learning methods in multiple classifications and recognition tasks recently, the supervised methods leveraged deep learning methods to discover an optimal electrical equipment defect feature representation scheme and corresponding classifier. Nordeng et al. [3] proposed a DEBC detection based on Fast-RCNN. Pan et al. [4] introduced a power line detection method based on CNN and Hough transform. However, supervised methods still suffer from the class imbalance problem. Such imbalance leads the
training is inefficient because most locations are negatives, which contribute no useful learning signal. Meanwhile, the generalization ability of the final model is also destroyed.

To address the above mentioned drawback, we propose an improved YOLOv3 method for electrical equipment defect detection in this paper. The main contributions of this work are two-folds. (1) the Complete Intersection over Union (CIOU) is introduced into Non-Maximum Suppression (NMS) process to promote defect detection performance. (2) Focal loss function is adopted to train the Convolutional Neural Networks (CNN) to make better use of the easy training examples.

2 Method

2.1 YOLOv3

The framework of YOLOv3 is shown in Figure.1. By applying a residual skip connection, YOLOv3 solves the vanishing gradient problem of deep networks. The up-sampling and concatenation mechanism make YOLOv3 keep the fine-grained features for small object detection. When an image is sent into the network, the object detection process is performed at three different scales with the similar manner. And the predicted results of these three detection layers are combined and processed using non-maximum suppression. After that, the final detection results are determined. Meanwhile, compared with the two-stage object detection methods, YOLOv3 detect multiple objects with a single inference, and its detection speed is therefore extremely fast. All these advantages make YOLOv3 suitable for multi-targets detection in complex electrical scenes.

![Figure 1. The framework of YOLOv3.](image)

2.2 NMS with CIOU

NMS is the last step in object detection algorithms. During NMS, redundant detection boxes are removed if its overlap with the highest score box exceeds a threshold. The criterion of bounding box regression is essential for the performance of NMS. Intersection Over Union (IOU) is widely adopted in the existing methods. The formula of IOU is shown as follow.

\[
\text{IOU} = \frac{|B_n B_t|}{|B_u B_t|}
\]  
(1)
where $B = (x, y, w, h)$ is the predicted box and $B^{gt} = (x^{gt}, y^{gt}, w^{gt}, h^{gt})$ is the ground-truth. $l-norm$ loss is adopted on the coordinates of $B$ and $B^{gt}$ to measure the distance between bounding boxes. Based on IOU, the IOU loss is defined as

$$LOSS_{IOU} = 1 - IOU$$

(2)

It is obvious that IOU loss only works when the bounding boxes have overlap, and would not provide any moving gradient for non-overlapping cases. As an improvement of IOU, the Generalized IOU loss (GIOU) adds a penalty term on traditional IOU. However, this makes the GIOU take more iterations to converge, especially for horizontal and vertical bounding boxes. The experiment results show that the GIOU loss cannot well converge in electrical equipment defect detection, yielding inaccurate detection.

To solve this problem, we introduce a Complete IOU (CIOU) loss, in which three geometric measures, i.e., overlap area, central point distance and aspect ratio, are combined for bounding box regression. The CIOU is defined as

$$LOSS_{CIOU} = 1 - IOU + \frac{\rho^2(b, b^{gt})}{c^2} + \alpha \vartheta$$

(3)

where the trade-off parameter $\alpha$ and aspect ratio consistency parameter $\vartheta$ are calculated as

$$\alpha = \frac{\vartheta}{1 - IOU + \vartheta}$$

(4)

$$\vartheta = \frac{4}{\pi^2} \left( \arctan \frac{w^{gt}}{h^{gt}} - \arctan \frac{w}{h} \right)^2$$

(5)

By combining three important geometric measures, CIOU generates faster convergence and better performance than IOU and GIOU losses.

### 2.3 Focal loss

The equipment defects are scarce in the practical electric power inspection, and this situation leads a serious class imbalance problem for defect detection. These detectors evaluate 10000 candidate locations per image but only a few locations contain objects. The imbalance brings inefficient training process and degenerate models. A common solution is to perform some form of online hard example mining (OHEM), in which the training images are sampled according to a non-uniform, non-stationary distribution that depends on the current loss of each images under consideration. Such strategy puts more emphasis on misclassified examples, but completely discards easy examples.

In this paper, we introduce focal loss strategy to deal with the class imbalance problem. The loss function applies a dynamical scaler on cross entropy loss, when the confidence of correct class on samples increases, the scaling factor decays. Such method can automatically down-weight the contribution of easy examples during training and focus the model on hard examples rapidly. The focal loss is defined as follow.

$$FL(p_t) = -(1 - p_t)^\gamma \log(p_t)$$

(6)

where $(1 - p_t)^\gamma$ is the modulating factor applied on cross entropy loss and $p_t$ is defined as

$$p_t = \begin{cases} p & \text{if } y = 1 \\ 1 - p & \text{otherwise} \end{cases}$$

(7)

The above-mentioned focal loss function can differentiate between easy examples and hard examples, avoid the easily classified negatives comprise the majority of the loss and dominate the gradient.

### 3 Results

The electrical equipment dataset come from State Grid Intelligent Technology Co., Ltd, this dataset has been widely employed in electrical equipment default detection research area. The complete dataset contains 11631 images of normal equipment and defective
equipment. In our study, 10631 images are selected randomly for algorithm training and the rest 1000 images construct the testing dataset for performance evaluation. Experiments are carried out in Ubuntu16.04 operating system based on NVIDIA Tesla P4. For three type of typical electrical equipment defects, the performance of the algorithm can be assessed by the statistical measures of Recall, Precision and Average Precision.

In our experiments, various of bounding box regression strategies are employed on YOLOv3 network and the performance (Recall and Precision) is reported in Table 1. It can be noticed that GIOU achieves a certain degree of performance improvement. CIou, which takes three important geometric factors of two bounding boxes into account, brings obvious performance gains. The last row of Table 1 displays the average of Recall and Precision, CIou method can improve the performance with gains of 3.7% Recall and 4.3% Precision. Representative detection results are shown in Figure 1. It is shown that the detection box by CIou loss is more accurate than that by traditional IOU loss.

Table 1. Defect detection results of YOLOv3 using different IOU methods.

| Defect type     | Recall (%) | Precision (%) |
|-----------------|------------|---------------|
|                 | IOU        | GIOU | CIOU | IOU | GIOU | CIOU |
| metal corrosion | 61.8       | 62.2  | 65.7 | 51.3 | 47.6  | 54.0 |
| pin missing     | 77.5       | 79.1  | 83.0 | 80.0 | 74.4  | 76.9 |
| oil leakage     | 85.4       | 86.6  | 87.2 | 73.9 | 83.2  | 87.1 |
| average         | 74.9       | 76.0  | 78.6 | 68.4 | 68.4  | 72.7 |

Figure 2. Detection examples using YOLO v3 with IOU and CIou.

To understand the focal loss better, YOLOv3 with traditional loss function, OHEM and focal loss are employed on electrical equipment default detection separately. The quantitative outputs are shown in Table 2. The proposed method using focal loss achieves 78.20% Recall. In contrast, the OHEM achieves 76.43% Recall. This is a gap of 1.77%, showing FL is more effective than OHEM for training dense detectors.

Table 2. Defect detection results of YOLOv3 using different loss function.

| Defect type     | Recall (%) | Precision (%) |
|-----------------|------------|---------------|
|                 | baseline   | OHEM | FL | baseline   | OHEM | FL |
| metal corrosion | 61.80      | 63.5  | 66.3  | 51.30      | 54.9  | 55.40 |
| pin missing     | 77.50      | 78.90 | 80.10 | 80.00      | 82.4  | 82.20 |
| oil leakage     | 85.40      | 86.90 | 88.20 | 73.90      | 76.30 | 79.60 |
| average         | 74.90      | 76.43 | 78.20 | 68.40      | 71.20 | 72.40 |

We compare the proposed method with recent state-of-the-art object detection methods including YOLOv3, SSD and Faster-RCNN. Results are presented in Table 3. Compared to existing methods, our approach achieves a 1% AP gap (0.783 vs. 0.793) with the closest competitor, Faster-RCNN.
Table 3. Experimental results (AP) based on different methods.

| Method        | metal corrosion | pin missing | oil leakage | average |
|---------------|-----------------|-------------|-------------|---------|
| YOLOv3        | 0.618           | 0.819       | 0.865       | 0.767   |
| SSD           | 0.629           | 0.836       | 0.872       | 0.779   |
| Faster-RCNN   | 0.632           | 0.841       | 0.876       | 0.783   |
| The proposed method | 0.648           | 0.853       | 0.878       | 0.793   |

4 Discussion

How to make the bounding box regression is still an open problem for NMS, which is the critical step for object detection procedure. In this paper, we introduce the CIOU loss for bounding box regression in YOLOv3, leading to faster convergence and better performance in electrical equipment defect detection.

From the perspective of machine learning, the class imbalance problem is the biggest challenge for automatic defects detection work. OHEM is the common method to deal with such problem. The focal loss function we proposed in this work pays more attention to the easy samples. It can be found from Table 2 that the recall and precision of metal corrosion with FL are generally higher than that of baseline and OHEM. In addition, the low computation burden of the proposed method makes it suitable for developing a real-time defect detection system.

5 Conclusions

In this paper, we propose an automatic electrical equipment defect detection method based on improved YOLOv3. For one thing, Complete IOU(CIOU) is introduced into NMS, getting faster convergence and more accurate object location. For another things, focal loss is employed to deal with the class imbalance problem during the electrical equipment defect detection. Electrical equipment dataset is used for performance evaluation and the proposed approach obtains competitive performance compared with other object detection methods.

References

1. P. S. Prasad, B. P. Rao. LBP-HF features and machine learning applied for automated monitoring of insulators for overhead power distribution lines. International Conference on Wireless Communications. 808-812 (2016).
2. S. M. Liu, X. J. Xu. Substation Intelligent Monitoring System Based on Pattern Recognition. Communications in Computer & Information Science (2011).
3. I. E. Nordeng, A. Hasan, D. Olsen, et al. DEBC detection with deep learning. 20th Scandinavian Conference on Image Analysis (SCIA). 248-259 (2017).
4. C. Pan, X. Cao, D. Wu. Power line detection via background noise removal. IEEE Global Conference on Signal and Information Processing. 871-875 (2017).
5. S. Abhinav, G. Abhinav, G. Ross. Training Region-Based Object Detectors with Online Hard Example. IEEE Conference on Computer Vision and Pattern Recognition (CVPR). 761-769 (2016).