Flame Recognition based on Yolov5 Algorithm

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Abstract

To address the problem of low accuracy and speed of flame detection, this paper proposes an improved YOLOv5 for flame detection. The new network is based on YOLOv5 by changing the loss function to DIoU(Distance Intersection over Union). Through introducing a large number of training data sets, it is hoped to improve the object detection accuracy. The experimental results show that the proposed YOLOv5 algorithm is effective with higher accuracy and faster detection for different flames.

Keywords: Flame Recognition, YOLOv5, deep learning, computer vision

1. Introduction

Since the flame was used by human beings, it brings people not only convenience, and convenience followed by all kinds of disasters caused by flames. If the fire did not develop into a serious fire detection and extinguishment in time, can effectively prevent the occurrence of fire, reduce the loss of fire to people. Therefore, the early detection of fire is very important.

In recent years, computer vision has become a very hot research and learning direction, and many fields have begun to use computer vision to help improve work efficiency. When using computer vision for flame detection, many defects of traditional instruments can be reduced. It has the advantages of fast response, wide detection range and less environmental pollution. Compared with traditional fire detection methods, it has wider prospects. However, these new methods are still immature and need to improve their detection accuracy. Different algorithms need to find different characteristics of the flame, such as color, motion, shape, frequency, texture and other aspects to judge whether the result is correct, and then combine with the existing deep learning algorithm, finally become a set of completed flame recognition technology.

Object detection algorithms based on deep learning are mostly divided into Two ideas. One is two-stage method, in which a candidate frame is formed and objects in the candidate frame are detected by algorithm. The other is the one-stage method, which integrates the whole detection process together and directly presents the detection results, such as YOLO (You Only Look Once) series[1-3] and SSD(Single Shot MultiBox Detector) series[4]. YOLO series detection algorithms have been developed since 2016, and the detection accuracy has been significantly improved.

2. YOLOv5 Network

YOLOv5 model is a recently proposed neural network model, which performs very well in target detection tasks. Excellent results have been achieved in both COCO and VOC datasets. YOLOv5 network structure is shown in Fig. 1.

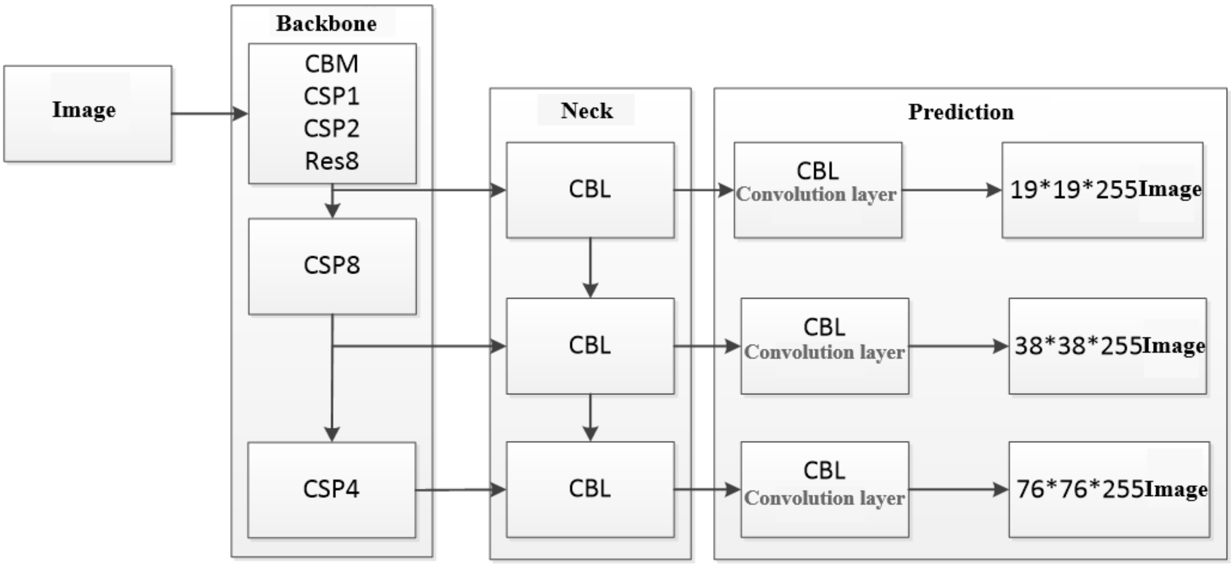

Fig. 1. YOLOv5 network structure

2.1. *Improved regression loss function*

DIoU loss is to reintroduce a penalty term $R(B^p, B^{gt})$ on the basis of IoU loss, so the calculation formula of DIoU loss is:

$$L_{DIoU} = 1 - IoU + R(B^p, B^{gt}) \tag{1}$$

Where $R(B^p, B^{gt})$ is the penalty term:

$$R(B^p, B^{gt}) = \frac{\rho^2(b^p, b^{gt})}{c^2} \tag{2}$$

$\rho(\cdot)$ is the Euclidean distance, b^p and b^{gt} represent the center point of the prediction frame B^p and the real frame B^{gt} respectively, and c is the diagonal length of the minimum area covering the prediction frame B^p and the real frame B^{gt}.

As shown in Fig.2, the green box is the target box, the black box is the prediction box, and the gray box is the minimum area covering the two boxes. d is the distance between the center point of the prediction box and the real box, and c is the diagonal length of the gray box, namely the value of variable c in Formula 2.

Like GIoU loss, the loss value of DIoU loss is still not related to size. Furthermore, DIoU losses can be further optimized in cases where the prediction box does not overlap with the real box. Different from GIoU loss, DIoU can minimize the distance between the center point of the prediction box and the real box, which greatly speeds up the convergence of the loss.

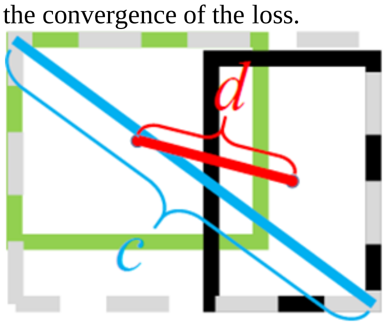

Fig. 2. Schematic diagram of DIoU

3. Construction of Flame Detection Model

In this experiment, a large number of data are used to train the improved YOLOv5.

3.1. *Experiment preparation*

LabeImg was selected as the image annotation tool. The annotation principles are as follows: label bright flame edge; The outline of smoke that can block the object is marked, and the other cases are not marked. A total of 14,649 training sets and 3,767 verification sets were used in the training of this model, which were labeled as fire. The flow chart of YOLOV5 model training is shown in Fig.2.

3.2. *Tests and results*

After the successful training of the model, a model can be obtained to detect random flame images, which can output the position information and confidence of the image to be detected in the form of a label box on the image. The specific results of the target detection task are shown in the figure. The rectangular box represents the position of the flame, and the text above represents the classification and confidence of the target. Fig. 3 is the output of several test images:

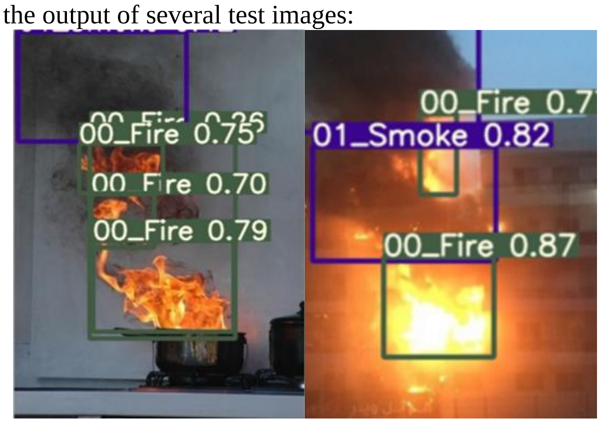

Fig. 3. Flame detection result

Take the picture on the left as an example, the green rectangular box represents the detected target position, 00_Fire in the picture represents the target in the rectangular box is flame, and 0.70, 0.79 and other numbers represent confidence.

4. Conclusion

In this paper, computer vision is used to realize the identification of flames in various Spaces, and flames in video clips can be detected in real time. Specifically, after the video image data captured by each camera is collected, the image is labeled first, and then sent into the neural network for model training. Finally, the flame image can be labeled on the random input to output flame information.

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