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Research Article

A lightweight pedestrian vehicle detection algorithm based on YOLOV5

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ABSTRACT

With the continuous improvement of social development level, traffic has become complicated. Therefore, the detection of pedestrian and vehicles becomes important. There are many application scenarios for pedestrian-vehicle detection, such as autonomous driving and transportation. This paper mainly introduces the research status of pedestrian-vehicle detection, analyzes the advantages and disadvantages of various current target detection algorithms, and focuses on YOLOv5 algorithm. Because the YOLOv5 model is much smaller than YOLOv4, and YOLOv5 also has strong detection ability. Finally, YOLOv5 is used to carry out pedestrian-vehicle detection experiments. The results the detection accuracy is improved slightly.

1. Introduction

Object detection is one of the important branches of artificial intelligence. It has been continuously updated in the past 20 years, so it is the epitome of the long-term development of computer vision. Target detection algorithms are mainly divided into three categories: traditional target detection algorithms, classifier-based detection algorithms and regression-based detection algorithms.

In terms of pedestrian and vehicle detection. Initially, the pedestrian detection algorithm mainly used independent single features for feature selection in videos and pictures, and it was mainly aimed at pedestrians in social streets [1]. The most commonly used feature selection in China is the histogram of directional gradients (HOG). Its core point is that some appearances and features of the detected object can be better represented by the distribution of gradient and edge direction. Traditional foreign target detection methods mainly explore target classification, such as how to distinguish pedestrians from other objects in the street and how to use classifiers reasonably. In vehicle detection, the more commonly used method is for researchers to establish information and non-redundant derived values from the initial measurement data. The advantage of this method is to promote learning and improve the generalization ability of the model, and it can also bring better interpretability.

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2. Target Detection Algorithms

Target detection algorithms can be divided into traditional target detection algorithms, classifier-based detection algorithms and regression-based detection algorithms.

2.1. *Traditional target detection algorithm*

SIFT is the Scale-invariant feature transform, which is proposed in the Distinctive Image Features from Scale-Invariant Keypoints paper by David G. Lowe et al. The SIFT algorithm can extract its invariant characteristics from the features when the image proportion and rotation are unchanged.

AdaBoost is an iterative algorithm. The principle of the algorithm is to use a large number of single-layer decision trees for reasonable integration. It adds a new weak classifier in each round until it reaches a predetermined small enough error rate.

2.2. *Detection algorithm based on classifier*

OverFeat is an early stage one-stage target detection method. This method mainly discusses multiscale and sliding window methods. It can be used in a feedforward network that includes convolution calculations and has a deep structure.

The R-CNN (Region with CNN features) algorithm was previously implemented on the Pascal-VOC 2012 dataset and was further optimized. It is a single and quantifiable algorithm that significantly improves mAP (mean Average Precision) value by nearly 30% (the experimental result at the time was 53.5%). R-CNN algorithm is a type of recurrent neural network that takes sequence data as input, recursively in the evolution direction of the sequence, and all nodes (recurrent units) are connected in a chain. After that, Fast-RCNN and Faster-RCNN were proposed on the basis of R-CNN.

2.3. *Regression-based detection algorithm*

YOLO (You Only Look Once) is an algorithm that can solve bounding boxes with accurate predictions while using convolutional sliding windows [2]. The core idea of YOLO is to transform target detection into a regression problem, using the entire image as the input of the network, and only going through a neural network to get the location of the bounding box and its category. The YOLO algorithm can realize real-time detection.

Compared with the YOLO algorithm, the SSD (Single Shot MultiBox Detector) algorithm directly uses CNN for direct detection. The algorithm uses convolutional feature maps of different scales for detection. Large-scale feature maps can be used to detect small things, and small-scale feature maps can be used to detect large objects, so that objects of different scales can be detected.

The shortcomings of the SSD algorithm are mainly in two aspects. On the one hand, it is necessary to manually set the initial scale and aspect ratio of default boxes. The basic size and shape of default boxes in the network cannot be obtained directly by learning, but need to be set manually. The size and shape of the default box used by each layer of features in the network are different, which makes the debugging process very dependent on experience.

On the other hand, the algorithm is still relatively poor for small-sized target recognition, and it does not reach the level of Faster R-CNN. Because SSD uses conv4_3 low-level features to detect small targets, and the low-level features have few convolutional layers, there is a problem of insufficient feature extraction.

3. YOLOv5 and Improvements

3.1. *YOLOv5*

Compared with YOLOv3, YOLOv5 has innovated in four parts of the network structure.

3.1.1. Input

(1) Mosaic data enhancement
This method randomly zooms, cuts, and arranges four pictures randomly, turns them into a new picture, and then puts the new picture into the network for learning.
(2) Adaptive anchor frame
In the early stage of training, a predefined frame will determine the location of the target at a possible location. As the training progresses, the real frame will gradually shift based on the preset frame for construction. Calculate the best anchor frame value in different training sets adaptively.

3.1.2 Backbone

The focus layer is very similar to adjacent downsampling. Suppose there is a 4x4 picture that is concatenated with separated pixel values into four 2x2 pictures. This structure can avoid information loss, the number of channels has become 4 times the original, and the size is half of the original.

3.1.3 Neck

Inserting the Neck layer between the input layer and the Backbone layer improves the ability to extract fusion features. Can better detect targets of different sizes.

3.1.4 Output

Bounding box is used in YOLOv5. Bounding box is to fine-tune the predicted box to make it close to the ground truth box.

3.2. *Improvement*

3.2.1 BN and RBN

Batch norm is batch normalization [3]. It is to complete the normalization by adding parameters during the training process to solve the problem of normalized learning features. When applying Batch Norm, it should be satisfied that the mutual characteristics of different instances completely obey the same distribution. However, the distribution characteristics of the test set instances and the training data cannot be consistent. Therefore, the inconsistency in the training and testing process will weaken the actual effect of the BN layer.

In order to solve the above problems, this article quotes the method of RBN (Representative Batch Norm). RBN mainly takes two main steps: centering calibration and scaling calibration.

(1) Centering Calibration

$$X_{cm(n,x,h,w)} = X_{(n,c,h,w)} + W_m \cdot K_m \quad (1)$$

In Eq. (1), X is set as the input feature W_m is set as a learnable weight vector, and K_m is expressed as an example feature. This article uses GMP (Global Max Pooling). The learnable variable Wm is set to (N, C, 1, 1). '·'stands for dot product operation, which mainly converts two features into the same shape and then performs dot product operation.

(2) Scaling Calibration

In the next step of Batch Norm, specifically, before the stretching adjustment, do the image scaling and alignment related operations.

In the experiment, the BN layer was replaced with RBN to test its training effect in the YOLOv5 network.

3.2.2 Ghost model network

Many compression models have been proposed in recent years, such as MobileNet series, ShuffleNet series, etc. Huawei's Noah's Ark Lab has proposed a new network architecture whose performance exceeds Google's MobileNet series, named "GhostNet".

The core idea of GhostNet is to use cheap operations to replace ordinary convolution operations to generate these redundant feature maps. The Ghost module divides the ordinary convolution into two parts. First, it performs an ordinary 1x1 convolution, which is a small amount of convolution. For example, a 32-channel convolution is normally used. Here, a 16-channel convolution is used. The effect of this 1x1 convolution Similar to feature integration, the feature enrichment of the input feature layer is generated. Then we perform deep separable convolution. This deep separable convolution is layer-by-layer convolution, which is the cheap operations we mentioned above [4]. It uses the feature enrichment obtained in the previous step to generate a Ghost feature map. Using the Ghost Net network can reduce the amount of model parameters and increase the execution speed of the model while ensuring a good detection effect. The Ghost model is shown in the Fig 1 below.

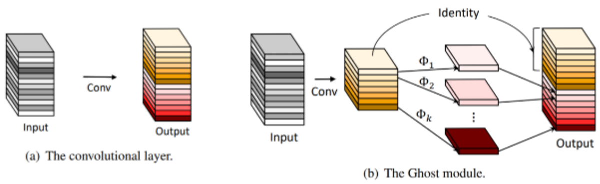

Fig.1. Ghost model schematic

Backbone has a relatively strong feature extraction ability for images, so try to modify it in this structure. Since the number of feature mapping layers of the GhostNet network is the same as that of the conventional convolution, it is more convenient to apply it in the neural network of YOLOv5. In this experiment, the conventional Conv convolution is mainly changed to GhostConv, and the rest of the network structure remains unchanged. The modified location is shown in Fig 2.

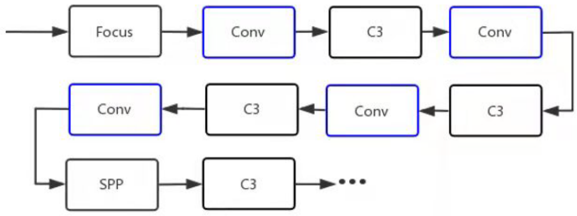

Fig.2. Modify the structure location diagram

4. Experiment and Result Analysis

4.1. *Experimental equipment*

The experimental equipment is shown in Table 1.

Table 1. Device-related configuration

Name	Version and Model
Ubunt version:	20.04.3 LTS
CUDA version:	11.2
Graphics:	GeForce GTX 1080 Ti
Frame:	Torch

4.2. *Data collection*

The preliminary data preparation mainly calibrates two categories, pedestrian and vehicle. Through repeated screening and data supplementation, 30938 images of the data set and corresponding label files are provided, script codes are written, and the training set and the test set are allocated according to a 9:1 ratio. There are 27761 training sets and 3177 verification sets. Write script code to retain the specified label content (0-person, 1-car).

4.3. *Experimental setup*

In order to find a better learning rate and explore its relationship with the model training effect, first set the batchsize to the maximum value that the server GPU memory can hold, set to: 62, the GPU memory usage (11057MiB / 11178MiB), and set the learning rate lr1=0.1, lr2=0.05, lr3=0.01, lr4=0.005, lr5=0.001, compare mAP of different categories. The experimental results are shown in Table 2.

Table 2. Learning rate comparison

	lr1	lr2	lr3	lr4	lr5
Person	0.856	0.862	0.867	0.867	0.861
Vehicle	0.943	0.947	0.949	0.945	0.936
All classes	0.899	0.905	0.908	0.906	0.898

It can be seen from Table 2 that the model works best when lr=0.01.

4.4. *GhostNet network performance comparison*

The following uses the original network to compare with the network after adding the Ghost model, and mainly evaluates indicators such as FLOPs, the number of network layers, the amount of parameters, the inference time, and the size of the model. The experimental results are shown in Table 3.

Table 3. Model parameter comparison

Model	FLOPs	Layers	Parameters (M)	Inference/NMS/Total	Model size
Original model	16.4	283	7.06	7.7/7.8/15.4	30.9MB
Ghost model	14.6	303	6.32	7.6/6.8/14.4	30.8MB

It can be seen from Table 3 that after introducing the Ghost model, FLOPs, layers, Parameters, inference results and model size are reduced.

4.5. *Experimental result*

The size of the convolution kernel restricts the amount of calculation of its model. Adjust the depth to separate the convolution kernel size, set g=1 and set the default kernel size to 5*5, respectively, adjust to 1*1 (point-by-point volume Product), 3*3 observe its model size and performance. The experimental results are shown in Table 4.

Table 4. Network performance of different sizes of deep separable convolution kernels in Ghost mode

Convolution size	FLOPs	Time(H)	Parameters (M)	Model size	mAP@.5 mAP@.5:.95
1*1	14.5	14.7	6.283	27.8MB	0.900;0.626
3*3	14.5	16.6	6.287	27.8MB	0.901;0.629
5*5	14.6	19.4	6.295	30.8MB	0.905;0.632

As shown in Table 4, different convolution kernel sizes affect the amount of parameters and the size of the mAP. The larger the convolution kernel, the larger the mAP, and the amount of parameters will increase accordingly. The pedestrian-vehicle detection effect of the YOLOv5 network is shown in the Fig 3.

Fig.3. The result of recognition by model

5. Concluding

In terms of algorithms, although YOLOv5 is relatively complete, it can still be optimized through lightweight ideas (pruning, distillation) to improve the flexibility of model deployment [5].

n addition, the transformer that shines in the field of NLP can now be applied to target detection. It provides a new idea for target detection to transform the detection problem into a set-based index problem, which is different from the traditional replacement of the backbone or the addition of a special FPN. If the attention mechanism can be properly combined with the YOLOv5 network, there may be better performance. This is also a research direction in the future

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