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Analysis and Application of Concave Neural Network Algorithm for Recognition of Road Garbage

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ABSTRACT
In order to select the optimal road surface debris detection algorithm and maximize the detection effect of garbage, this paper compares the recognition effects of several convolutional neural network algorithms on road debris. Firstly, in view of the shortage of the existing road garbage obstacledatabase, thedata set is used to expand the data set, andthen establishthe road garbage obstacle database RGOD, and the image automatic labeling tool is proposed in data preprocessing. Finally, the database is tested using different convolutional neuralnetwork algorithms, and the test results are compared. The test resultsshow that the Faster-RCNN algorithm hasbetter detection effect than the SSD algorithm for the existing road garbage obstacle dataset, and the false detection and miss detection are reduced. After adding the network of the Feature Pyramid Networks (FPN), the recognition accuracy of the algorithm for small objects is improved byabout10%. FPN uses the features of the low-level and high-level features to classify and locate, and makes full use of the feature maps ofdifferent scales to improve thedetection effect of small objects.
Keywords: *Object detection; convolutional neural network algorithm; road waste database; data enhancement; automatic labeling.*

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I. INTRODUCTION

With the development of artificial intelligence, all walks of life are tending to automation and intellectualization, while the automobile industry is more significant. The realization of L2, L3 and other industry standards marks the preliminary realization of passenger vehicle intellectualization. However, the intellectualization of commercial vehicles is rarely mentioned. Most of the road sweepers used at this stage need manual operation, low level of intelligence, and time-consuming and laborious. In recent years, the rapid development of object detection in machine vision provides a basis for the realization of intelligent road sweeper replacing traditional sweeper manual operation.

The object detection is a challenging work in machine vision [1]. Because the object has different morphological characteristics in different angles and distances, together with external interference factors such as illumination and occlusion during imaging, these situations pose a great challenge to the task of object detection, so it is very difficult to detect the object accurately. The main contents of this paper are as follows:

(1) The application of object detection technology in machine learning to intelligent urban road sweeper is proposed. Faster-RCNN object detection algorithm [2] and SSD object detection algorithm [3] are applied to the classification of road refuse obstacles.

(2) In view of the shortage of existing garbage database, data enhancement technology is used to design and create RGOD database of road garbage obstacles. This paper proposes to use automatic image annotation tool in data preprocessing, which greatly reduces the task of manual annotation.

(3) Using different algorithms to test and compare in the database RGOD, and then analyzing the test results to select the best recognition and detection algorithm suitable for road rubbish.

II. ALGORITHM

2.1 SSD

SSD (Single Shot MultiBox Detector) is a single-time multi-object detection algorithm. With VGG16 as the basic network structure, the design concept of a priori frame is introduced,and adds the multi-scale convolution layer on the basis of VGG16 to obtain multiple feature maps with different resolutions for object detection. The framework structure is shown in Figure 1. The concept of Faster R-CNN region is adopted: in the process of detection, a large number of candidate regions are used as ROI (Region of Interest) [4]; and the regression idea of YOLO algorithm is also used: in a encapsulationnetwork, the object position and type are directly returned. The area concept can be used to extract feature maps with different aspect ratios; the regression idea effectively simplifies the computational complexity of the neural network and improves the detection speed.

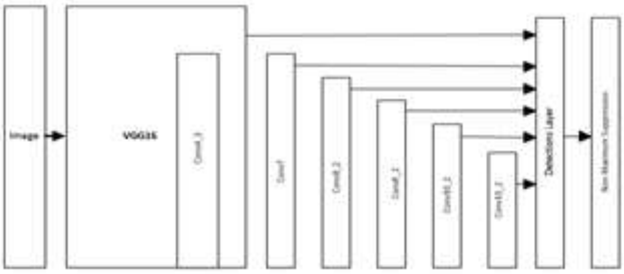


Figure 1. SSD algorithm framework diagram

2.3 Faster-RCNN

Faster-RCNN is a new object detection method consisting of two modules.The first module extracts the region recommendation box from the RPN (Region Proposal Networks) convolutional neural network; the other module is based on the Fast-RCNN region recommendation box, which mainlyused to generatehigh-quality recommendation area by end-to-end training of RPN, and then gives it to Fast-RCNN for detection.

The implementation steps of Faster-RCNN are as follows: 1) Feature extraction through CNN network to generate feature map; 2) area recommendation network RPN uses softmax activation function to calculate the probability that each feature point in the feature map belongs to the object (foreground), and at the same time generates several candidate regions of different sizes at the corresponding location of the original map;3) the ROI pooling layer mappingthe candidate regions into feature vectors of fixed dimensions, and then uses the softmax function to perform Object class judgment in the candidate regions. The formula for calculating softmax function is as follows.

$$S_i = \frac{e^{y_k}}{\sum_{i=1}^{k} e^{y_k}} \qquad (1)$$

In the formula, the category label y can take k different value, which the training setis $\{(x^{(1)}, y^{(1)}),...,(x^{(m)}, y^{(m)})\}(y^{(i)} \in \{1,2,..., k\})$.

Figure 3. Faster-RCNN flow chart**Figure 4.**Faster-RCNN frame diagram

III. DATA PREPROCESSING

3.1 Sample Library Establishment

In-depth learning algorithm training generally requires a large number of high-quality data and pictures as data sets. A small amount of data can easily lead to over-fitting, which seriously reduces the final test results. The existing road garbage database is made by taking photos and sampling from the actual road. There are only more than 1000 pictures in the early stage of the database, which obviously can not meet the training requirements of the data volume.

This paper chooses to use Imgaug tool to implement data enhancement [5].Imgaug is a library for image enhancement in machine learning experiments. It supports a variety of basic image transformation and enhancement technologies. While realizing a variety of image transformation methods, it can combine these transformations in any order to create new transformation types. Figure 5 represents the image date enhancement. RGOD, a database of road rubbish obstacles designed and created in this paper, contains 12 kinds of common rubbish on the road. There are 6997 images of rubbish. The sampling conditions of the images include the main changes of illumination, location and shape. RGOD is a large-scale road garbage database that we have established. To a certain extent, it makes up for the deficiencies of domestic large-scale garbage database and has strong practical significance. In the data preprocessing process, the total data sets are randomly classified, 3780 pictures are used as training data sets, 880 as validation data sets, and 500 as test data sets.

Figure 5. Image data enhancement

3.2 Picture Annotation

Image annotation (labeling) has always been an important step in deep learning object detection, but manual image annotation is a tedious and time-consuming task. It takes at least half an hour to label 100 images, which is obviously unrealistic for a large amount of data, so automatic image labeling emerges as the times require.

This article uses the automatic image annotation tool: semi automatic image annotation tool [6], which trains existing datasets based on the Retina Net model, and then uses the pre-trained RetinaNet model to generate suggestion boxes from the test images. The model test results are shown in Figure. 6. Obviously, most of the objects can be detected.

Training the images of RGOD to get its own pre-training model and modify the label category name in the config.py configuration file, so that various kinds of rubbish classification can appear in the labeling tool. As shown in Figure 6, most of the garbage can be identified. It is difficult to identify the garbage with low resolution in the image correctly, so it is very important to recognize the correct effect and the accuracy of the model.

Figure 6. Garbage images are automatically labeled

IV. TEST RESULTS

4.1 Road Obstacle Detection Index

For object detection of road obstacles, commonly used metrics are used: MeanAverage Precision (mAP). The average accuracy of a certain type of garbage $AP_{(q)}$ is

$$AP_{(q)} = \frac{\sum P_{(q)}}{N_{(q)}} \quad (2)$$

$N_{(q)}$ represent all the pictures of the category that exist on the validation set.

Take the average of the average precision values for all categories Q_R on the validation set, mAP.

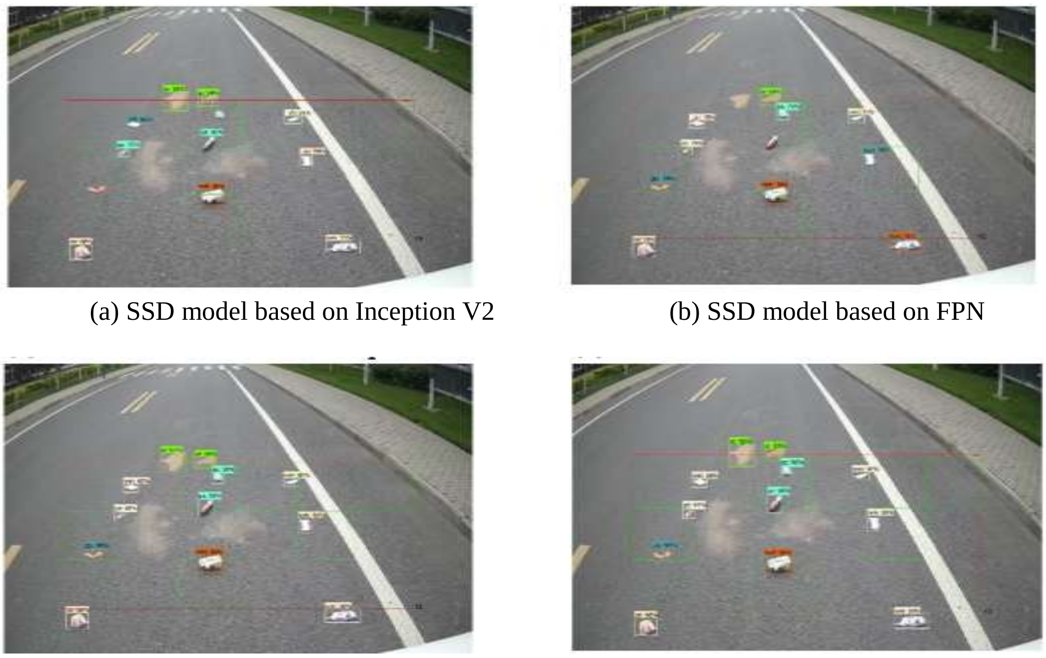
$$mAP = \frac{1}{|Q_R|} \sum_{q \in Q_R} AP(q) \quad (3)$$

Speed is another important evaluation index of the object detection algorithm. Only when the speed is fast enough can the real-time detection of the image be realized, which is extremely important for the real-time application of the obstacle detection. A common indicator for evaluating speed is Frame Per Second, which is the number of pictures that can be processed per second. The greater the number of images processed per second, the faster the model is.

4.2 Test Results and Analysis

In the experimental stage of this paper, the SSD and Faster-RCNN object detection algorithms based on Inception V2and FPN frameworks are selected for comparison. The test image detection results are shown in Figure. 7.

In Figure 7, different types of garbage obstacles correspond to different color recognition frames. Sand (st) can be well identified in figure (a) (b) (c) (d), but the false detection rate of SSD model is obviously increased in the same white milk carton (nnh) and packaging carton (bzh), the detection effect is poor, and the detection effect of Faster-RCNN is better. At the same time, the comparison of (a) and (b), (c) and (d) shows that the detection effect of the algorithm has been improved, the mAP of SSD algorithm has been improved by 13%, and Faster-RC has been improved.



(a) SSD model based on Inception V2 (b) SSD model based on FPN

(c)Faster-RCNN model based on Inception V2 (d)Faster-RCNN model based on FPN

Figure 7. Different model test result

Table 1Comparison of test results of different algorithms

Method	Backbone network	Speed（FPS）	mAP(%)
SSD_Inception_v2	Inception_v2	2	70.3
SSD_FPN	VGG16+FPN	21.7	83.3
Faster-RCNN_Inception_v2	Inception_v2	5.5	86.0
Faster-RCNN_FPN	VGG16+FPN	19.4	93.2

V. CONCLUSIONS

To solve the problem of inaccurate detection results of road rubbish obstacle recognition based on convolution neural network algorithm, this paper designs two ways to improve the recognition accuracy: expanding the database and selecting the optimal algorithm. In the process of selecting the algorithm, the feature pyramid FPN network structure is also added, which makes it introduce multi-scale feature connection structure on the basis of the original model. FPN integrates multi-scale information, and low-level semantic information enhances the feature utilization of small objects, retains low-resolution original information, and improves the utilization rate of high-level and low-level feature maps. The experimental results show that the Faster-RCNN algorithm is more suitable for the detection of road rubbish, and its mAP is at least 86%. If the running speed is neglected, the mAP of Faster-RCNN algorithm based on FPN framework can be increased to 93.2%. The recognition of road rubbish obstacles can be basically completed. However, from the test pictures, we can see that the recognition effect of some stacked garbage is only about 60%, such as stones (sz). Therefore, future research should focus on further improving the accuracy and robustness of stacked garbage detection, incorporating more semantic information of overlapping objects into the model, and recognizing the unique shadow overlapping area characteristics of overlapping objects, so as to improve the heap. The estimated probability of stacked garbage can improve the accuracy of stacked garbage in the identification of road garbage.

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