Detection of Parking Spaces in Open Environments with Low Light and Severe Weather

Borui Li(✉)

Computer Science and Engineering, University of New South Wales, Sydney 2052, Australia
z5292519@ad.unsw.edu.au

Abstract. Based on the goal of improving the accuracy of all-day outdoor parking lot detection, and considering the difficulty of detecting small spatial targets in many images and the problem that the detection performance at night has a large gap with that at daytime, the all-day outdoor parking lot detection algorithm is improved on the basis of the existing SSD algorithm. Firstly, the input image is amplified and sampled and data processed; then the VGG16 backbone feature extraction network of the SSD model is replaced by the ResNet101 residual network. The gradient problem that occurs with the deepening of the network training is avoided, thus enabling the feature map to extract richer image information. For the nighttime detection problem, the author is inspired by the SID model to train a new nighttime model using YOLO in one dataset, and then distill the features of the SSD model that has been trained using daytime images by SID. The new model has the potential features of SSD and YOLOV3 respectively, and can directly test outdoor parking images throughout the day, so that the new model finally has both daytime and nighttime features. The new model also has higher detection accuracy than other models by experimental comparison. Finally, the bonding layer responsible for fusing the models, reduces the total amount of computational resources, so the weights of the models are also improved.

Keywords: deep Learning · object detection · parking space detection · knowledge distillation

1 Introduction

With the growth of China's economy, the number of cars in China has grown significantly compared to the years 2000 to 2010, and the growth rate has been increasing in recent years. According to Big Data, by the end of 2021, the number of motor vehicles in China will reach 395 million. Excluding end-of-life vehicles, the number of cars on the road has grown even more than last year and is now over 300 million. At the same time, with the increase in the number of cars comes the problem of parking.

According to the ratio of parking spaces to car ownership, China has a shortage of at least 80 million parking spaces. Therefore, in the face of such a huge number of cars, there is still a huge gap in parking demand, so the contradiction between parking

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supply and demand is increasingly intensified. However, traffic congestion is inevitable in cosmopolitan cities, especially in the rush hours during the morning and evening, when the traffic flow on the main roads reaches its maximum. Meanwhile, the shortage of car parking spaces has become one of the important factors causing traffic congestion. In addition to well-managed parking lots such as underground garages, there are many outdoor parking lots that cannot accurately count every parking space due to backward management and lack of parking information, which not only aggravates the parking difficulty problem but also does not help drivers to get accurate information about parking space occupancy. Therefore, there is great room for the development of smart parking business.

Based on the application of a series of new technologies such as big data, artificial vision, and deep learning, the smart parking business has a fear of urban parking resources and realized functions such as parking space status inquiry, parking space reservation, and automatic parking, which play an important role in relieving traffic pressure. From 2009 to 2021, China's smart parking industry market also shows a rapid development trend, with a compound annual growth rate of 23.35%. In the smart parking business, parking space detection in outdoor parking lots is a very important research topic. The research involves the use of algorithms in images or videos to accurately determine whether a parking space is occupied or not, which not only helps drivers quickly locate the location of a parking space, but also largely solves the congestion that occurs when a large number of cars are looking for outdoor parking lots in parking lots. This research topic is of great significance to the traffic management of congested parking lots in China.

In the research algorithm, the traditional target detection uses the sliding window method, which leads to constant errors, while with the rapid development of deep learning, the extraction of image features by deep learning convolutional neural network can better achieve the target detection effect and can improve the data set and reduce errors, which is important for target detection. Ordinary deep learning target detection algorithms can detect parking spaces very accurately in good light conditions. However, when the outdoor weather environment is variable, such as rainy days, cloudy days and nights, the difficulty of extracting image features increases and the model detection effect becomes worse, which affects the model detection accuracy. Therefore, this paper improves the existing deep learning-based detection algorithm for parking space detection in complex and variable outdoor scenes to improve the detection performance (i.e., detection accuracy).

2 Method

2.1 Residual Module Structure Used

As shown in Fig. 1 (a), the trunk network is mainly composed of three parts. The first part uses 1×1 convolution layer to compress the dimensional features of the image, the second part uses 3×3 convolution layer to change the size of the convolution kernel, and the third part uses 1×1 convolution layer to change the number of channels. On the backbone network, the third part uses four times as many convolution kernels. In Fig. 1

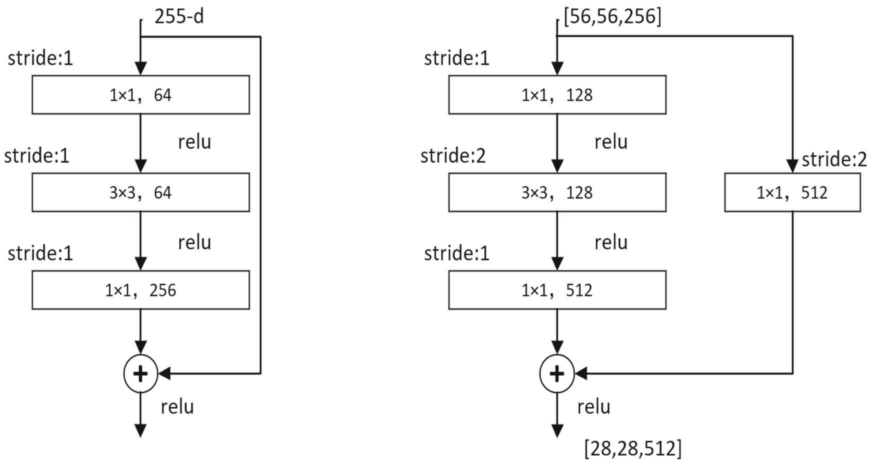

Fig. 1 Residual block structure (credit: original)

(b), there is also a leap-forward branch. In terms of the number of convolution kernels, the first part and the third part are the same, and the step spacing is 1.

2.2 SSD Network Model

SSD algorithm is one phase target detection algorithm, which is frequently used. It is different from the previously common target detection algorithm, the previous target detection algorithm is through a variety of convolution, after testing in the deep branch network, but with the characteristics of the pyramid of SSD algorithm, the multiple dimensions of character on target detection. The SSD algorithm extracts 6 different detection branches in the process of convolution, and the feature graphs of each detection branch are different in size. These feature graphs detect targets of different sizes. The SSD algorithm can predict 8732 frames in the original image, among which 5776 are small target prediction boxes. Therefore, this paper adopts SSD algorithm as the base algorithm to improve the detection of small target parking spaces.

The network model of SSD algorithm is shown in Fig. 2. It makes some modifications to the original VGG16 feature extraction network by changing the original two fully connected layers of VGG16 into the convolution layer (FC6 and FC7), removing the Dropout layer and FC8 layer, and adding a new convolution layer. The feature map obtained from each convolution layer can be directly entered into the detector to classify and predict the target.

2.3 SID Model

As the images of outdoor parking lots at night are affected by low light and low signal-to-noise ratio, the images become blurred and unrealistic, which seriously affects the feature extraction effect of existing image detection models and the detection effect is unsatisfactory. Although there are many image enhancement or noise reduction methods,

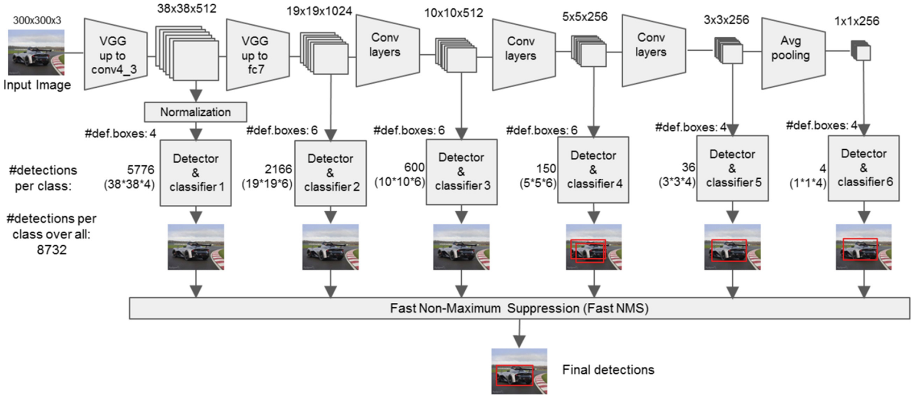

Fig. 2 SSD Model Structure (credit: original)

they are limited in some extreme cases. The SID (See In The Dark) model is an end-to-end network structure for processing extreme low-light images based on a fully convolutional neural network. The SID network is based on a U-net, which consists of an encoder and a decoder. Inspired by SID, we use this coder-decoder structure to further denoise the input daytime parking features, which serves to preserve as much information about the parking spaces themselves as possible.

2.4 YOLO Network

YOLO V1 algorithm is to put the target image into the input layer, and then extract the feature through the 1×1 and 3×3 convolution layer, then detect the category with the output of the full connection layer, and finally get the predicted target by regression classification in the output layer. YOLO V2 [9] improves the accuracy and speed on the basis of YOLO V1 [3]. It adds batch normalization [15] (BN) layer to each convolutional layer. After the model is trained, a high-resolution image classifier is used to slightly adjust the model, effectively reducing the impact of instant resolution switching. In terms of specific improvements, YOLO V3 [10] uses multi-scale detection, similar to FPN to detect feature maps, which can detect small targets more accurately. It also uses DarkNET-53 basic network, which is faster than ResNet [4], and no longer uses Softmax to classify prediction boxes. Because Softmax is used to deal with dichotomies, and many targets are multi-label. But on the whole, the detection performance is far better than YOLO V2.

2.5 All-day Parking Space Detection Algorithm

As shown in Fig. 3, the parking space detection algorithm of outdoor parking lot in daytime uses the idea of the single-stage SSD detection algorithm for reference. Different from the two-stage algorithm, the SSD algorithm directly predicts and coordinates the predicted target through linear regression, and the algorithm analyzes the target size at multiple scales, greatly improving the performance of small target detection. Considering

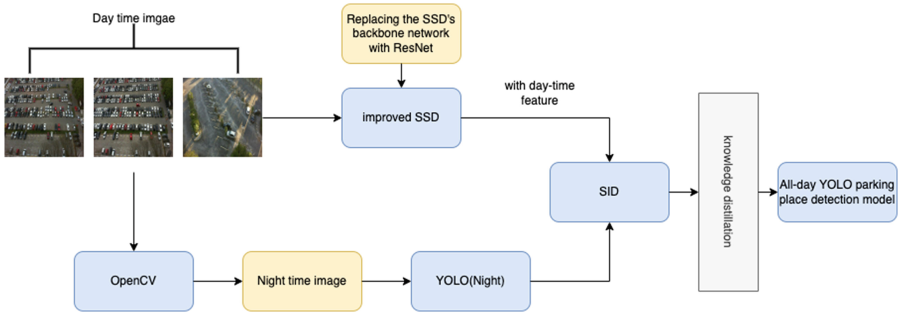

Fig. 3 The pipeline of all-day parking space detection (credit: original)

that parking lots are affected by different weather factors in outdoor scenarios, it is difficult to detect small target parking spaces. This paper adopts SSD model with better detection effect on small target as the basic model for improvement.

Under the night outdoor scene, outdoor parking lot parking image would suffer from a serious shortage of light, the image brightness is low, the influence of ordinary detection model in detecting precision is greatly decreased, the model for feature extraction of image space becomes difficult, it is needed to improve the existing model in order to enhance the detection precision of outdoor parking spaces at night.

This approach mainly adopts a method of fusion model, considering that continued use of SSD model as part of the fusion model will lead to increase in parameters of the fusion model and serious decrease in calculation speed. YOLO V3 [1] can improve the model detection speed while ensuring the accuracy difference is not very large, which is more suitable for fusion model than SSD. Therefore, we are inspired by the SID model [2] and use the codec structure of UNET to input the daytime features trained by SSD into Encoder, and then glue the YOLO trained using nighttime data after Decoder to combine the daytime and nighttime features, so as to achieve the ability to improve the detection of car parking spaces throughout the day.

3 Experiments

3.1 Experimental Environment and Parameter Setting

The experimental hardware configuration in this paper is Intel(R) Xeon(R) Gold 5218R CPU @ 2.10 ghz,

10-core CPU, 64GB memory and NVIDIA GeForce RTX 3090 independent graphics card. The software environment is Windows 10 operating system. The algorithm is based on PyTorch framework, using PyTorch 1.70 and CUDA 11.0.

In the experiment, the experimental parameter set in this paper was batch_size = 16, the learning rate was set to 0.001, and adjusted to 0.0001 after 50 epoch, training 100 epoch in total. Val_loss automatically ended the training without decreasing for many times, indicating that the model basically converges. The data in the experiment were divided into 70% training set, 10% verification set and 20% test set, among which the training verification set accounted for 80%.

Table 1. Comparative experiment of feature extraction network (credit: original)

Backbone	mAP (%)
VGG16	62
ResNet34	86.2
ResNet50	89.4
ResNet101	91.6

Table 2. Comparative experiments of all-day parking space detection algorithms in outdoor parking lots

Method	mIoU
YOLO	90.1
SSD	90.3
Faster-RCNN	91.2
Detnet	92.1
Ours-big	93.2

3.2 Introduction to Data Sets

The data set used in this paper is the data set of parking lot [21] as experimental data, which contains three different parking lots. As the whole data set contains three scenarios of sunny day, rainy day and cloudy day, outdoor empty parking spaces will be affected by illumination to varying degrees. In order to verify the reliability of the experiment, the empty parking spaces under three different weather conditions are used as training set and test set. In the case of sunny days in the adopted data set, there are 16,524 non-empty parking spaces and 14,372 empty parking spaces. Under the condition of occlusion, there were 6986 non-empty parking spaces and 15076 empty parking spaces; On rainy and cloudy days, please have 1041 non-vacant parking spaces, and 2553 vacant parking spaces. Different samples are shown in Figs. 4 and 5.

3.3 Experimental Results

3.4 Analysis of Experimental Results of Daytime Detection Algorithm

(1) Comparative experiment of feature extraction network

Replace the original VGG16 network with a ResNet residual network on an improved SSD network. In order to prove the effectiveness of residual network in this algorithm, VGG16, ResNet50 and ResNet101 are respectively used as the backbone feature extraction network of SSD detection algorithm, and the comparison test is conducted in the parking lot of public data set under the condition that other parameters remain unchanged.

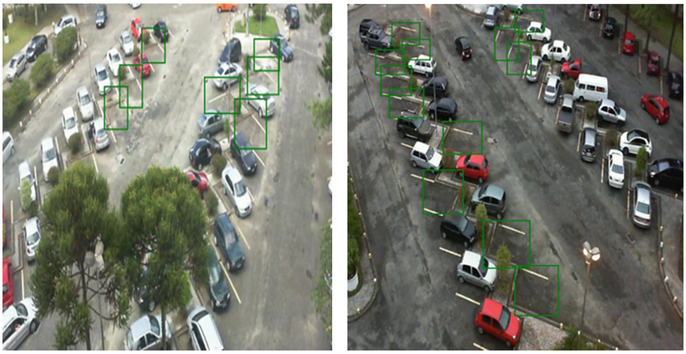

Fig. 4 Daytime recognition results (credit: original)

According to the Table 1, ResNet residual network has a better detection effect, among which ResNet101 reaches 91.6%, while other networks have a poor detection effect. The possible reason is that the training depth is not enough. Residual network improves the training depth and extracts better feature maps. This experiment verifies the validity of SSD feature extraction network using ResNet101.

(2) Comparative experiments of all-day parking space detection algorithms in outdoor parking lots

To verify the effectiveness of the algorithm for detecting parking spaces in outdoor parking lots during all-day, the proposed algorithm is compared with SSD, YOLO, DetNet and Faster RCNN. Considering that the nighttime scene is different from the daytime scene and the image darkness is slightly higher, a new model fusion with SID model and YOLOv3 model is performed by knowledge refinement. To improve the detection accuracy of nighttime outdoor parking lots, 2024 images of nighttime outdoor parking lots were generated by open CV based on the parking lot dataset as the test set of the model. As shown in Table 2, compared with other algorithms, the mIoU of the improved algorithm proposed in this paper is the highest, reaching 95.4%. Through experimental verification, SID and YOLOv3 are combined by knowledge refinement to achieve the purpose of improving detection accuracy.

4 Conclusion

At present, the research on parking space detection algorithm of outdoor parking lot is one of the key researches using deep learning to deal with parking space detection, and it is also the top priority of the application research of unmanned driving, vehicle volume recognition, automatic parking and so on. In this paper, the outdoor parking spaces are taken as the research object, and the parking space images in different scenes are used to judge whether the parking space is empty. This method can be applied to the actual scene by combining with the hardware system or APP. In the actual parking process, the driver can accurately know the specific vacant parking space information through the

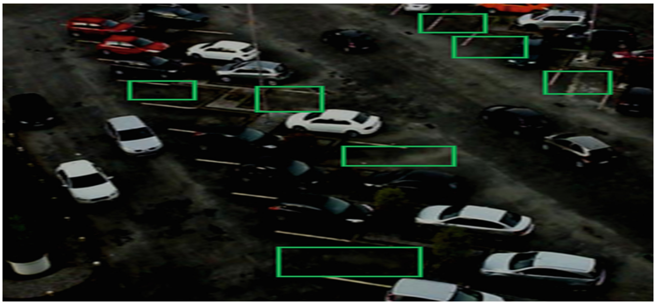

Fig. 5 Nighttime recognition results (credit: original)

intelligent system or APP, eliminating the blind search for parking space, thus reducing the unnecessary traffic pressure in the parking lot.

The data set used in the experiment in this paper is the parking lot data set with all kinds of weather, and the deep learning research method is used to detect image targets, achieving target detection in various outdoor scenes, and achieving objective improvement in accuracy compared with the original unimproved method. The main contents of this paper are as follows:

(1) According to the needs of outdoor parking space detection, the use of deep learning related knowledge of outdoor parking lot parking space detection is studied, through the experimental comparison and analysis, two different detection methods is put forward to deal with the outdoor parking lot parking space detection, and their structures and algorithm processes are introduced at night and during the day.
(2) The parking space detection algorithm for outdoor parking lots has a large number of small target parking spaces. Firstly, the method of data enhancement is used to over-sample the image data, which can generate more small targets in the image for the model to learn and enrich the feature extraction ability of the model. Then, the VGG16 backbone network in THE SSD network is replaced with a residual network to better solve the deep degradation of the SSD network. Finally, the improved SSD detection network proposed in this paper has significantly improved the accuracy compared with the original SSD network and other detection networks through experimental comparison and analysis.
(3) Since outdoor scenes also include nighttime scenes, and the dataset used in the experiments does not contain nighttime scenes, based on this paper, we propose an all-day outdoor parking space detection model, which does not require additional nighttime training datasets, and can also do detection at night with better accuracy through model fusion. We fuse the YOLO model trained with nighttime data with the SSD model through the Encoder-Decoder structure of SID. The SID model enables enough daytime image features to be learned by the YOLO model to complete all-day parking space image detection. Through experiments, the fusion model significantly improves the detection accuracy of nighttime outdoor parking images after training. Through the comparative analysis of experiments, the fusion model proposed in this paper greatly reduces the computational effort compared with the

case without fusion, which not only improves the detection accuracy at night, but also achieves the lightweight of the model.

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