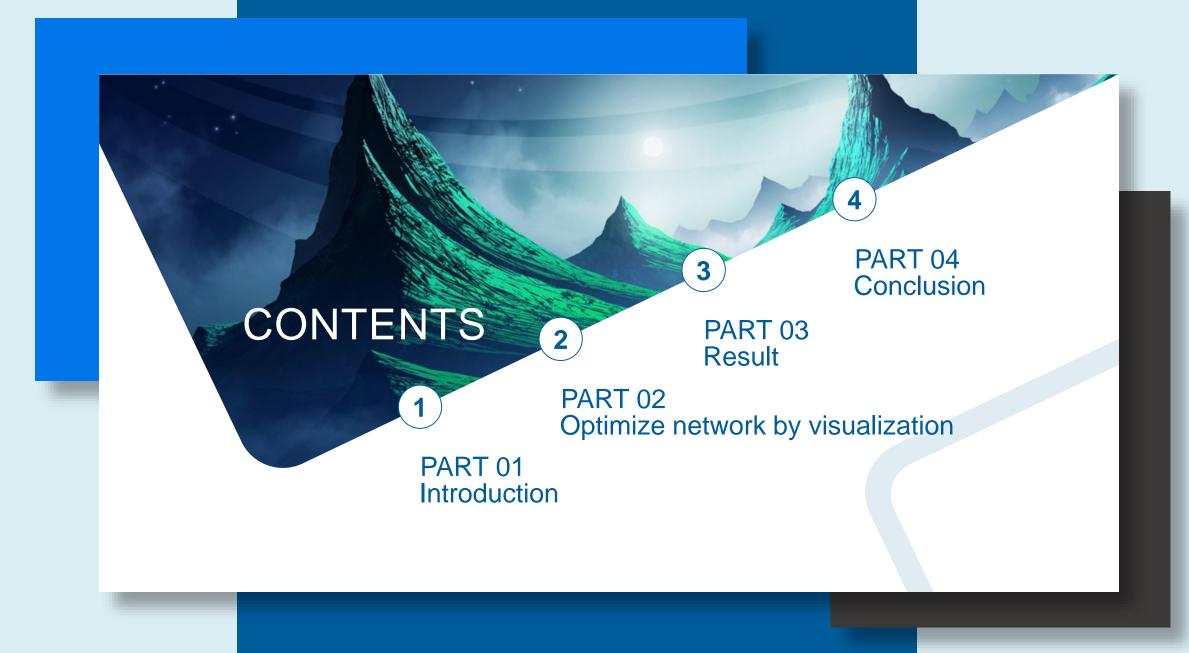
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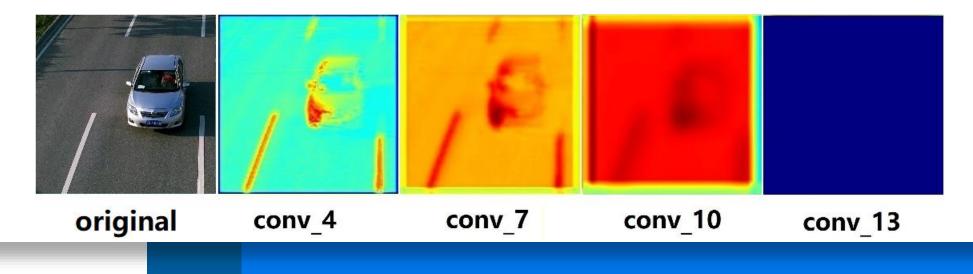
Research on Vehicle Detection based on Visual Convolution Network Optimization

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Abstract

Aiming at the problem that the vehicle detection algorithm based on convolutional neural network is too deep in the network layer, resulting in low training efficiency, this paper proposes a visualization method to adjust the structure of convolutional neural network, so as to improve training efficiency and detection effect. Firstly, the existing convolutional neural network model for image classification is visualized by using the middle layer visualization method. Then, the layers of the convolutional neural network model are analyzed to select the layer with the best visualization effect for network reconstruction, so as to obtain a relatively simplified network model. The experimental results show that the similar multi-target detection method proposed in this paper has obvious improvement in training efficiency and accuracy.





Introduction

Vehicle detection has been playing an important role in parking lot management and intersection monitoring and is an indispensable part of intelligent transportation.





Vehicle classification and traffic flow statistics of highway video are problems of moving object detection, identification and tracking, which can be realized by traditional image method and modern deep network.

Interferences of photos

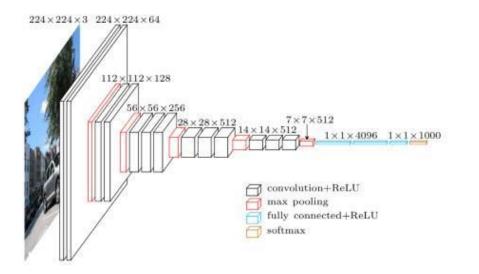




PART02 Optimize network by visualization

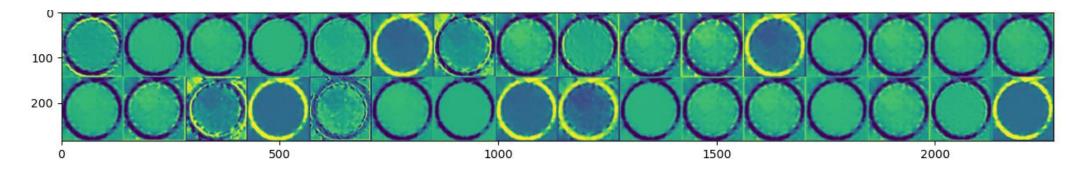
Structure of VGG-16

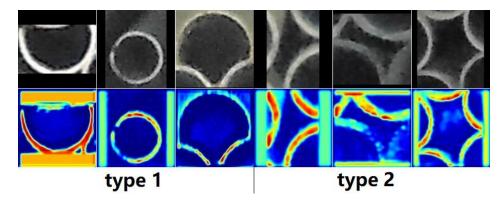
Vgg-16 has a clear structure, which is convenient for visual analysis of the effect of feature classification of targets at each layer. At the same time, the convolution kernel with the size of 3x3 is adopted. Under the same perception field, the smaller convolution kernel increases the network depth and reduces the number of parameters.



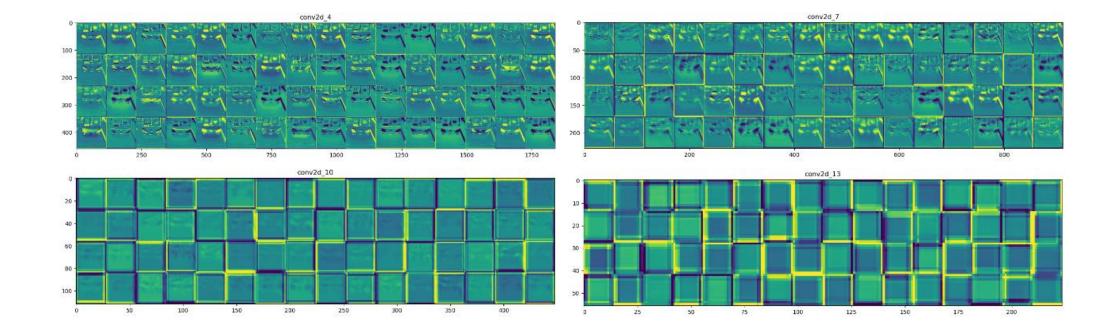
Visual analysis method

In this paper, the vehicle classification model is trained by VGG-16 network. The convolutional layer of the classification model is visualized through the activation diagram of the middle layer and the thermal diagram of the class activation. The network structure and depth that should be adopted are analyzed, so as to optimize the research object in this paper.

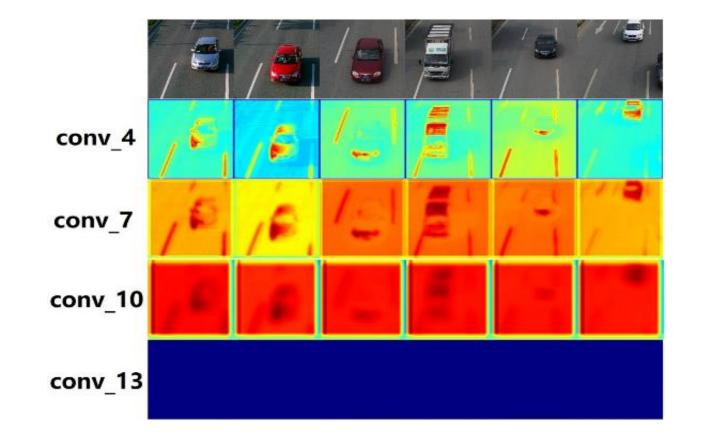




The middle layer activation diagram of VGG-16



The CAM of VGG-16

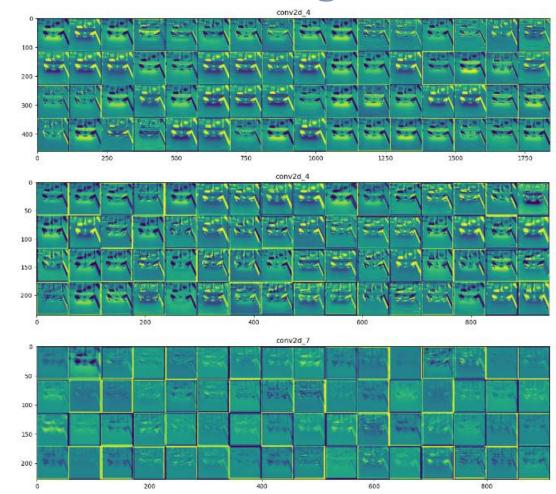


Optimize the network

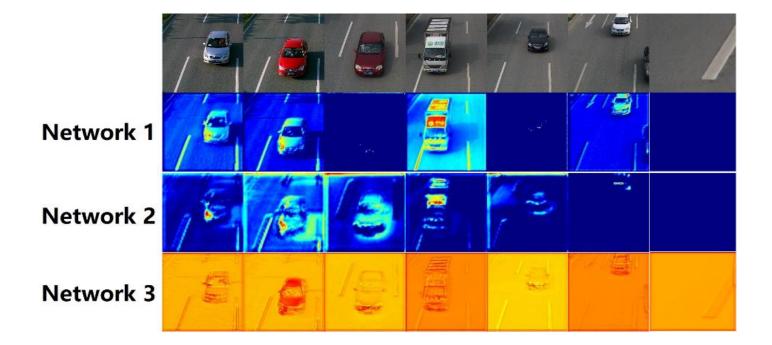
The VGG-16 network is too deep for the simple target detection in this paper, and the features cannot be extracted well. I chose the best network structure by visually comparing the three optimized training results.

Input	Input	Input
Conv3-128 conv2d_1 Conv3-128 conv2d_2	Conv3-64 conv2d_1 Conv3-64 conv2d_2	Conv3-64 conv2d_1 Conv3-64 conv2d_2
maxpool	maxpool	maxpool
Conv3-256 conv2d_3 Conv3-256 conv2d_4	Conv3-128 conv2d_3 Conv3-128 conv2d_4	Conv3-128 conv2d_3 Conv3-128 conv2d_4
maxpool	maxpool	maxpool
FC-1000	FC-1000	Conv3-256 conv2d_5
Softmax	Softmax	Conv3-256 conv2d_6 Conv3-256 conv2d 7
		maxpool
		FC-1000
		Softmax

The middle layer activation diagram









PART03 Result

Dataset and Evaluation

The Dataset adopted in this paper was the BIT-Vehicle Dataset. 7580 images were used as training set and 1371 images as test set after preprocessed.

The evaluation of this problem is divided into accuracy Acc, Precision and Re-call. Its calculation formula is as follows, and N_{TP} is correctly classified to positive samples, N_{FP} is incorrectly classified to positive samples, N_{TN} is correctly classified to negative samples, and N_{FN} is in-correctly classified to negative samples.

$$Acc = \frac{N_{TP} + N_{TN}}{N_{TP} + N_{FP} + N_{TN} + N_{FN}} \qquad Precision = \frac{N_{TP}}{N_{TP} + N_{FP}} \qquad Recall = \frac{N_{TP}}{N_{TP} + N_{FN}}$$

Result

Through the table, the recognition accuracy rate of network 2 adopted in this paper can reach 89.02% in actual use. Accelerate by Geforce RTX 2060 gpu, training process one iteration is used for an average of 55 s, compared VGG- 16 average round need 129 s, the training time reduced by 57.38%.

Networks	Acc(%)	Precision (%)	Recall(%)
VGG-16	87.96	95.70	89.25
Network 1	88.13	97.16	88.39
Network 2	89.02	98.03	88.71
Network 3	87.85	97.88	87.59



PART04 Conclusion

Conclusion

Aiming at the problem that the vehicle classification network layer is too deep in vehicle detection, this paper simplifies the VGG network model and eliminates unnecessary convolutional layer through the middle layer visualization technologyand CAM, so as to improve efficiency and reduce training cost. The experimental results show that the visualized optimization method of convolutional neural network is reasonable and effective to deal with the problem of Vehicle detection in this paper, and a good detection effect is obtained on the BIT-Vehicle data set.

At the same time, the method of visual adjustment of convolutional neural network proposed in this work has some short-comings. For example, after training, the convolutional neural network is manually adjusted through visualization, and in future studies, the subset selection method and other algorithms are used to automatically optimize the network.

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Thanks for watching!

(explainer: You Jingyang)