Research on Situation System Based on Big Data Image -- Taking Road Traffic as an Example

Yinghao Zhu¹,*, Jianxin Zhao¹, b, Xiaohang Li¹, c, Ning Yu², d and Yuqing Liu¹, e

¹Yisheng College, North China University of Science and Technology, Tangshan, China
²College of Electrical Engineering, North China University of Science and Technology, Tangshan, China

⁎1359573330@qq.com, b1377726718@qq.com, c1229822340@qq.com, d1540057990@qq.com, e593384267@qq.com

Abstract. In this paper, based on convolution neural network, object class awareness is carried out, Relu is selected as the activation function, which speeds up the training speed and overcomes the problem of gradient disappearance; using situation awareness technology and database technology, all object classes in the image scene are identified, and its location is specified. This paper takes the road traffic situation awareness system as the research object, and analyzes the information collection, processing and analysis process of the road traffic situation awareness system. CNN, R-CNN, Fast R-CNN and Faster R-CNN are used for vehicle classification and location recognition in road image big data.

1. Introduction
For the research of image situational awareness using convolutional neural network, Girsick R [1] and other scholars designed and implemented the R-CNN model, and the Fast R-CNN model proposed by Ren S [2] and other scholars improved the Faster R-CNN model at the algorithm level, which can be used for the feature map generated by sensing target categories and target positioning tasks.

In this paper, the application of convolutional neural network in road traffic situation awareness is studied. Combined with convolutional neural network, situation awareness technology, database and other technologies, a deep convolutional neural network model based on road traffic image big data is constructed. The vehicle classification and bit in road traffic image big data are carried out by CNN, R-CNN, Fast R-CNN and Faster R-CNN Location recognition and intelligent perception of road traffic conditions.
2. **Convolutional neural network**

![Convolutional neural network](image)

In the convolution calculation layer, each neuron is regarded as a filter, and the filter calculates the local data; in the excitation layer, the output results of the convolution layer are mapped nonlinearly, and the excitation function adopted is generally Relu; the pooling layer is sandwiched in the middle of the continuous convolution layer, which is used to compress the data and parameters, and the anyway data is over fitted; the neurons between each two layers are connected with weights, then, it is usually fully connected at the tail of convolutional neural network.

3. **Back propagation algorithm**

Training is the most important part of neural network. We need to know how the filter of the convolution layer looks for the edge curve, how to adjust the weight of the filter, and then introduce the back propagation algorithm [3]. Because the expression ability of linear model is not enough, we need to introduce activation function and add nonlinear factors. In this paper, we choose Relu as activation function. Relu function: accelerate the training speed and overcome the problem of gradient disappearance.

![Relu function](image)

This reverse transfer process effectively measures the error gradient of all connection weights in the network, and finally optimizes the parameters of each hidden layer by applying gradient descent algorithm.

Back propagation formula of output layer:

\[
\tilde{\theta}^L = f'(u^L)(y^n - t^n)
\]  

(1)
Error of output layer:

\[ E = \frac{1}{2} \sum_{k=1}^{L} (d_k - o_k)^2 \]  

Where \( d_k \) is the \( k \)-th layer of data samples, \( o_k \) is the layer of network output, input layer, output layer and hidden layer.

\[ \Delta w^r = -\eta \frac{\partial E}{\partial w^r} \]  

4. **Softmax classifier**

When detecting the feasibility of the model, it is more intuitive to convert the score obtained by classification into the probability value. In the neural network, the Softmax classifier is between the hidden layer and the output layer. The purpose of using the SoftMax function is to compress any real number vector of one \( K \) dimension into another \( K \) dimension real number vector, where each element value is between \((0, 1)\) [4].

Hypothetical function:

\[ h_\theta(x) = \frac{1}{1 + e^{-\theta^T x}} \]  

SoftMax function:

\[ \sigma(z)_j = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}} \]  

The SoftMax algorithm can be used to solve the problem of multi class classification, and the probability value of it can be estimated by the hypothesis function normalize the sum to 1.

The cost function of the model is:

\[ J(\theta) = -\log \left( \frac{e^{y^T \theta}}{\sum_j e^{f^T \theta}} \right) \]  

The training of SoftMax classifier is completed by minimizing the value of cost function. In general, the random gradient descent method is used to iterate several times after derivation, so as to make the result fall into the global optimal solution as much as possible. The above core algorithm can be used for better image recognition and classification. In order to achieve more intuitive system
convolution neural network effect in image target classification, CNN, R-CNN, Fast R-CNN and Faster R-CNN recognition effects are compared. The results are shown in figure 3:

![Figure 3. Image target category perception.](image)

5. **R-CNN model based on rolregin**

Kaiming He et al. Proposed a new network structure SPP net (Spatial Pyramid Pooling NetWork) [5]. For general size images, CNN model can solve the problem, but for the influence of any size, SPP net model can solve the problem well. In this model, a spatial sampling layer is added after the last convolution layer and before the first full connection layer. This layer contains a variety of size sampling windows, which solves the problem of any size image. It brings convenience to the analysis of road traffic.

The ROI (Region of Interest) network layer is proposed in the Fast R-CNN model based on SPP-net. The Fast R-CNN model uses the Selective search method to extract the target area. The reason why the Fast R-CNN model is different from R-CNN is that it will directly input the original image into the CNN model, only one feature extraction is needed, and the Fast R-CNN model will input a group of objects of the whole image Coordinates of candidate areas. For each region, the ROI sampling layer samples the features within the region to a fixed size, and classifies the coordinate regression of the output region position of a network layer. The combination of category recognition and coordinate position regression simplifies the perception process by using the classified supervision information and regression supervision information.

6. **R-CNN model based on RPN region**

Since the GPU platform is not used for accelerated calculation, the Selective search method limits the overall position sensing efficiency of the model. No matter the R-CNN model or the Fast R-CNN model, these problems cannot be solved. Therefore, the extraction of candidate regions becomes the bottleneck to limit the speed of position sensing of the target [6].

Because the efficiency of RPN is much higher than that of Selective search, the Fast R-CNN model is trained by using the target candidate region generated by RPN to improve the perception efficiency, which is the basic idea of Fast R-CNN model. By adjusting the network structure and training in stages, the Faster R-CNN optimization model is obtained.

In order to have a more intuitive effect of system convolution neural network on image target category, and to compare the recognition effects of CNN, R-CNN, Fast R-CNN and Faster R-CNN, the results are shown in figure 4:
7. System tese analysis
In the process of system performance test, the system response time and packet loss rate are used to test the concurrent performance of the system and the performance of responding to customers.

Limited to the influence of network environment and server performance on performance indicators, the network environment in the test process is selected as the internal network of road traffic center, the server is a single server with a new system and a cluster with two single servers, and the test tool is Mercury Load Runner. Using Mercury Load Runner to make concurrent access, we test the performance of the system in a single server environment and the system in a cluster environment, and collate the recorded data to get the results as shown in figure 5 and figure 6.

It can be seen from the test results that the number of concurrent services closest to the system is 400 in the single server environment and 700 in the cluster environment with two servers. The test results show that the system performance can meet the requirements, and can be reused in multi-system environment, and can further improve the performance through later expansion.

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