

Vehicle Road Scene Recognition Based on Improved Deep Learning

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Abstract:

In order to improve the recognition effect of autonomous vehicles on road scenes, the new proposed activation function ReLU sigmoid is proposed based on ReLU and sigmoid model solves the problem of neuron necrosis in ReLU model. By analyzing the action principle of activation function, the key points of activation function design are given, and sigmoid and ReLU are combined in the positive and negative half axes of semantic axis to optimize the road scene recognition model. Experiments on the zhengxin expressway data set show that compared with the ReLU and LReLU models, the ReLU sigmoid model effectively improves the recognition accuracy of the convolutional neural network for the road scene, from 75.12% and 67.15% to 83.70%. It is proved that the algorithm can improve the recognition performance of the deep learning model for the road scene and alleviate the phenomenon of neuron necrosis, and improve the vehicle's perception of the road environment.

Keywords: *Vehicle, Scene recognition, Deep learning, Activation function design, Convolutional neural network*

I. INTRODUCTION

In recent years, automatic driving technology has become a research hotspot in the field of vehicle engineering, and has great potential in ensuring driving safety, reducing traffic accidents and improving road capacity [1]. The automatic driving system consists of three parts: environment perception, path planning and decision control. Road scene recognition plays a key role in automatic driving technology, and has excellent road scene recognition ability, which can effectively improve the safety of automatic driving system. Image classification technology based on deep learning algorithm can be used for road environment recognition. Therefore, this paper classifies and recognizes road scene weather, road scene location and driving time. Although deep learning has achieved great success in image classification [2] and fault diagnosis [3], the data imbalance will still have an adverse impact on the deep learning method. Therefore, it is necessary to design a more robust recognition method for the unbalanced road scene data to further improve the vehicle's recognition ability of road scene.

II. DEEP LEARNING AND IMAGE RECOGNITION

Deep learning can better complete the task of image recognition [4], and has achieved good results in target detection [5] and image classification [6]. In fact, image classification technology can also be used

for road scene recognition.

In 1998, literature [7] first applied convolutional neural network to handwritten digit recognition, marking the beginning of deep learning in image recognition. In 2012, Alex-net proposed in document [8] has the basic characteristics of the current convolutional neural network architecture, and won the championship in the Image-net LSVRC-2010 competition with top-1 and top-5 error rates of 37.5% and 17%. After that, many excellent convolutional neural networks have been proposed one after another. For example, Xception [9] shows color in image classification, but its performance will still be affected by large-scale unbalanced data.

III. ACTIVATION FUNCTION

3.1 Activation Function Design

Activation function plays a key role in the development of deep learning theory. Activation function can improve the nonlinear expression ability of convolutional neural network and improve the performance of the network to solve nonlinear recognition tasks[10].

Deep learning has achieved great success in the task of road scene recognition, and one of the keys to further improve its recognition performance is to design a better activation function [10]. In reality, most recognition tasks are linear and inseparable. Adding activation function can improve the nonlinear expression ability of neural network model. Consider the basic unit neuron structure of neural network, as shown in Figure 1.

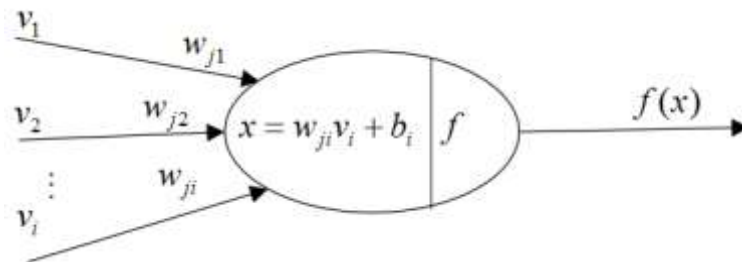


Fig 1: Single neuron with activation function

The input x of the neuron activation function is the sum of the product of each antenna input v and the weight w plus the offset value B . You input this result into the activation function f to generate neuronal impulse. Without the function of nonlinear activation function, the essence of classifier is only linear equation, which can not deal with nonlinear problems in real life.

In the early stage of the development of artificial neural network, sigmoid and Tanh activation functions are widely used in decision-making applications. Both of them are saturated activation functions, which are easy to produce gradient dispersion problem in the process of neural network training. In 2012,

Krizhevsky used modified linear units (ReLU) as the activation function in Alex net, and won the champion of image net competition in that year; The negative half axis of ReLU can make the output of some neurons zero, improve the sparsity of the network, reduce the dependence between parameters, and alleviate the occurrence of over fitting. Because of its simple calculation, the convergence speed of the model is accelerated, and the gradient of the x positive half axis is 1, which effectively solves the gradient dispersion problem of early activation functions such as sigmoid and Tanh. At the same time, because the negative half axis of ReLU is always zero, it leads to the necrosis of some neurons. Scholars have successively proposed Leaky-ReLU, ELU, PReLU and other improvement schemes. However, the additional super parameter α introduced by Leaky-ReLU and PReLU will slow down the convergence speed of neural network and increase the difficulty of training.

The improved activation function Sigmoid-ReLU proposed in this paper combines the sigmoid and ReLU functions in different ways on the positive and negative half axes of x , so as to ensure the gradient of the positive half axis and make the output of the negative half axis not zero at the same time. Experiments on the zhengxin expressway scene data set show that the proposed model can achieve higher road scene classification accuracy than Leaky-ReLU, ELU and other models, effectively alleviate the necrosis phenomenon of neurons, greatly reduce the loss of model classification and improve the performance of the model.

3.2 Classical Activation Function

The nonlinear activation function can be used to nonlinear express the input data and improve the characterization ability and recognition performance of the network. This section will discuss the classical activation function.

In the early stage of the development of artificial neural network, saturated S activation function is often used in decision-making, and the representative ones are sigmoid function and Tanh function (as shown in Figure 2). Sigmoid function is widely used in the early application because of its differentiability, which is suitable for back-propagation training algorithm. Its mathematical definition is:

$$\text{Sigmoid}(x) = \frac{1}{1 + e^{-x}} \quad (1)$$

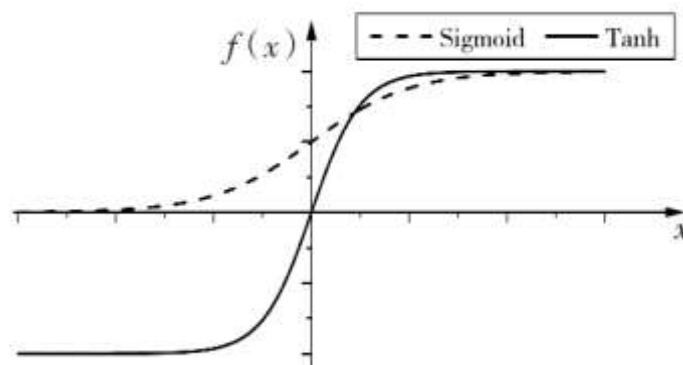


Fig 2: Sigmoid and Tanh Function Curve

However, when sigmoid is applied to the deep network, the non-zero center and constant positive output leads to only one update direction of the neural network weight, which affects the convergence speed and reduces the network performance. Moreover, when the input value tends to $+\infty$ or $-\infty$, the gradient of the function is close to 0, which means that in the process of back propagation, some neurons will reach saturation and cannot be trained effectively, The adjacent neurons are also trained very slowly, that is, the gradient diffusion problem. Tanh called activation function improves the convergence speed of the network to a certain extent, but it still can not effectively solve the gradient dispersion problem. The mathematical definition of Tanh function is:

$$\text{Tanh}(x) = \frac{1 - e^{-2x}}{1 + e^{-2x}} \quad (2)$$

3.3 ReLU Activation Function

In order to overcome the defects of the above saturated activation function, scholars have proposed the unsaturated activation function as a solution, and the most representative is the modified linear element (ReLU) [12]. At present, it has been the default activation function of many convolution neural network architectures. The mathematical form of the modified linear unit is concise, which is expressed as follows:

$$\text{ReLU}(x) = \max(0, x) \quad (3)$$

The gradient of ReLU before the x positive half axis is constant to 1, which effectively solves the gradient dispersion problem of saturated activation functions sigmoid and Tanh. Due to the simple discriminant calculation, the operation speed has been greatly improved. However, when the data falls into the negative half axis of ReLU, because its output is zero, some neural units will not be trained in the training process, which also causes the necrosis phenomenon of neurons, affects the representation ability of the model and reduces the recognition performance of the model.

3.4 Leaky ReLU Activation Function

In view of the neuron necrosis caused by ReLU, leaky ReLU (LReLU) can give a slope α to the negative half axis of ReLU. To avoid. However, some studies have found that the performance of LReLU is not stable. The mathematical definition of leaky ReLU (LReLU) is as follows:

$$\text{LReLU} = \begin{cases} x, & x < 0 \\ x, & x \geq 0 \end{cases} \quad (4)$$

The curves of ReLU, LReLU and sigmoid activation functions are shown in Figure 3. LReLU has a slope in the negative half axis, but the continuous change of LReLU in the training process is easy to cause the instability of training. Many experimental results have also proved this. Therefore, it is necessary to propose a new activation function with better performance.

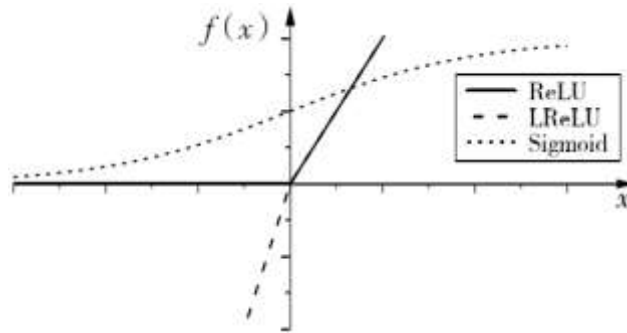


Fig 3: Function curve of ReLU, LReLU and sigmoid

3.5 ELU activation function

In order to solve the above problems, scholars also proposed the ELU activation function, with the mathematical form as follows:

$$LReLU = \begin{cases} x, & x > 0 \\ a(e^x - 1), & x \leq 0 \end{cases} \quad (5)$$

The ELU function curve is shown in Figure 4. In the experiment, it is found that the performance of ELU function is not significantly improved compared with ReLU.

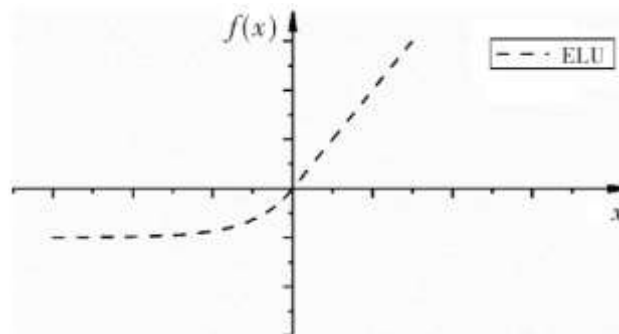


Fig 4: ELU function curve

IV. IMPROVEMENT METHOD OF ACTIVATION FUNCTION

Based on the discussion of common activation functions, combined with the characteristics of various activation functions, this section analyzes the action principle of activation functions, and puts forward an improved Sigmoid ReLU activation function.

The training process of convolutional neural network is mainly composed of forward propagation and back propagation. Forward propagation refers to the process that the input data is processed by a series of network layers to obtain the actual output; Back propagation obtains the loss by calculating the difference

between the forward propagation output and the expected output. The neuron parameters of each layer are updated by error back propagation method and chain rule to improve the fitting ability of the network model to the data and further reduce the forward loss. Next, taking the convolution layer as an example, the forward and back propagation algorithms of neural network are analyzed, and the action principle of activation function is analyzed theoretically.

4.1 Forward Propagation Process

In the forward propagation algorithm, after the upper layer input data is weighted, the input activation function generates the output value:

$$a^{i,l} = \sigma(z^{i,l}) = \sigma(a^{i,l-1} \times w^l + b^l) \quad (6)$$

In which: superscript express the channels number and network layers; w is convolution kernel; b is offset value; σ is the activate function.

It can be seen from equation (6) that in the forward propagation of convolution neural network, the function of activation function is to nonlinear process the results of convolution operation and improve the nonlinear expression ability of the network. Therefore, the activation function cannot be a constant or linear function, otherwise the number of layers is only linear expression, which is not conducive to the improvement of network performance.

4.2 Back Propagation Process

The back propagation process is a real parameter optimization process, in which each network layer will update the internal convolution kernel parameters and bias values. The loss value is obtained by calculating the difference between the forward propagation result and the expected value. The parameters are updated through the back propagation algorithm, gradient descent method and chain rule. The specific process is as follows:

(1) According to the actual needs, select the appropriate loss function J , such as Cross entropy loss function or mean square error loss function, and calculate the gradient error of the output layer δ^L :

$$\delta^L = \frac{\partial J(W, b)}{\partial z^L} = \frac{\partial J(W, b)}{\partial a^L} \odot \sigma'(z^L) \quad (7)$$

(2) The gradient error of convolution layer is calculated by mathematical induction $\delta^{i,l}$:

$$\delta^{i,l} = \delta^{i,l+1} \times rot180(W^{l+1}) \odot \sigma'(z^L) \quad (8)$$

(3) Update w and b according to equation (9)

$$W^L = W^l - \alpha \sum_{i=1}^m a^{i,l-1} * \delta^{i,l}, b^l = b^l - \sum_{i=1}^m \sum_{u,v} (\delta^{i,l})_{u,v} \quad (9)$$

In which: J is the loss function; \odot is the Hadamard product; a is the neuron output; α is the learning

rate; Subscript u and v are submatrix; Superscript is the neuron serial number and layers number.

From equation (7) (9), the following conclusions can be drawn:

(1) There is a linear relationship between the final parameter update value and the derivative of the activation function, which shows that the activation function will directly affect the parameter update and convergence speed of the convolution neural network model. In order to make the parameters of the neural network fall near the global optimal solution as much as possible, the derivative of the activation function in the initial stage should be large enough to accelerate the convergence of the model, and reduce the derivative in the second half to make the model converge smoothly;

(2) The direction of parameter update is related to the positive and negative of the input value of this layer and is directly related to the activation function. Therefore, the activation function should have non-zero output on both positive and negative axes.

To sum up, the designed activation function should meet the following conditions:

- (1) Nonlinear constant or linear expression;
- (2) There is non-zero output on both positive and negative half axes;
- (3) The absolute value of derivative presents the characteristics of "large first and then small";
- (4) Easy to calculate.

4.3 Sigmoid ReLU Activation Function

From the previous analysis, it can be seen that the ideal activation function should have a large derivative in the first half to accelerate the convergence of the network, while the derivative in the second half should be gradually reduced to make the network converge smoothly. The existing activation functions can not meet the above requirements, so we must combine the advantages of different activation functions and propose an improved activation function Sigmoid-ReLU.

ReLU is linear in the positive half axis, so the calculation is relatively simple and overcomes the gradient dispersion problem. However, due to the constant zero of the negative half axis, it increases the sparsity and "kills" some neurons at the same time; The derivative of Sigmoid activation function meets the characteristics of "large first and then small". Combining the characteristics of the two activation functions and optimizing the combination can improve the recognition performance of the network. Based on the above characteristics of sigmoid, ReLU and LReLU activation functions, this paper proposes an improved activation function, which is named Sigmoid ReLU. The mathematical definition is as follows:

$$Sigmoid - ReLU(x) = \begin{cases} \frac{1}{1+e^{-x}} + 0.5(x-1), & x \geq 0 \\ \frac{x}{1+e^{-x}}, & x < 0 \end{cases} \quad (10)$$

The design and analysis are as follows:

- (1) ReLU function is a partial linear model with less calculation and ensures the gradient in the positive

half axis of x , but it is easy to "kill" some neurons in the negative half axis. Compared with Tanh, Sigmoid improves the network training speed, but does not fundamentally solve the gradient dispersion problem of saturated activation function. However, because its derivative meets the characteristics of "first large and then small", it can ensure the convergence speed and make the convergence stable at the same time. Therefore, the combination of the two can accelerate the convergence speed and reduce the occurrence of gradient dispersion.

(2) In the positive half axis of x , the denominator term of sigmoid model is linearly combined with X , which can meet the requirement of "first large and then small" of the gradient of activation function in the positive half axis.

(3) At the first negative half axis of x , the sigmoid is multiplied by the first to ensure the non-zero output of the negative half axis. At the same time, the gradient of the activation function tends to zero at the negative infinity, which also meets the gradient requirements, improves the convergence speed and nonlinear expression ability of the network, and ensures the convergence stability at the same time. Compared with ReLU, in the negative half axis, x and $1/(1+e^{-x})$ are combined to make the function value gradually converge to 0 after reaching the minimum at a certain point, which increases the nonlinearity of the activation function and the nonlinear mapping ability of neurons; In the positive half axis of X , the sub term $0.5(x-1)$ is used to ensure the gradient of the positive half axis, and then added with $1/(1+e^{-x})$ to enhance the nonlinearity of the function. Compared with Sigmoid and Tanh functions, the model meets the gradient requirements while increasing nonlinearity.

In this paper, the function images of the activation function sigmoid ReLU and the activation functions of sigmoid, Tanh and ReLU are shown in Figure 5.

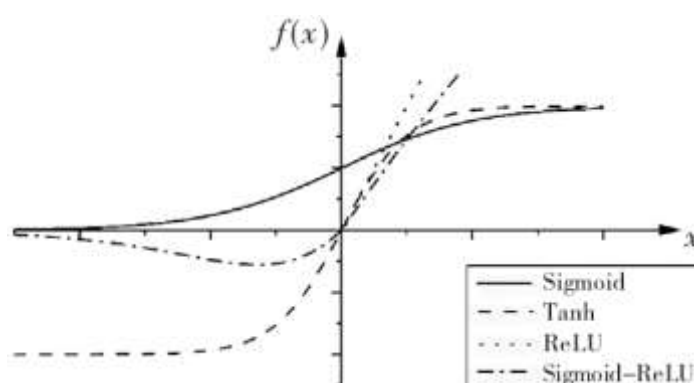


Fig 5: ReLU, LReLU and activation function curves

V. EXPERIMENTAL RESULTS AND ANALYSIS

5.1 Simulation Environment

The experimental platform is based on Win10 (64 bit) operating system and (GPU) Geforce GTX

1050ti hardware platform, and the algorithm is programmed and developed through tensor flow deep learning framework. This experiment uses the zhengxin expressway data set of the University of Berkeley. There are 69863 pictures belonging to 15 sub categories. The original resolution of the pictures is 1280x720. In order to reduce the computational cost, the pictures are uniformly scaled to 128 x 128[11-13].

5.2 Data Set

Remove the invalid labeled images and blurred images in the data set. Figure 6 is some sample images, including 3 categories of weather, place and time, with a total of 15 categories.

5.3 Deep Learning Model

In this paper, convolutional neural network is used to classify and recognize road scenes with different activation functions. The super parameters of network structure are shown in TABLE I. Where k represents the number of output categories.



Fig 6: Sample data set
(a) Weather conditions (b) scene location (c) time

TABLE I Convolutional neural network structure

Layer name	Kernel size	Step size	Pooling	Characteristic diagram
Input layer				132×132×4
Convolution layer 1	12×12×32	5×5		32×32×34
Standardization layer 1				32×32×34
Maximum pooling layer 1	4×4	2×2		16×16×3
Convolution layer 2	6×6×48	1×1	same	16×16×48
Standardization layer 2				16×16×48

Maximum pooling layer 2	4×4	2×2		6×6×48
Convolution layer 3	4×4×64	1×1	same	6×6×64
Maximum pooling layer 3	4×4	2×2		4×4×64
Global average pooling layer				4×4×64
Full connection layer				2×2×k
Output layer				2×2×k

5.4 Performance Evaluation Index

In the experimental stage, we use the training recognition accuracy and kappa coefficient to evaluate the performance of the algorithm.

5.5 Experimental Results and Analysis

In the experimental stage, the training accuracy of this activation function model is compared with Sigmoid, Tanh, ReLU, ELU and LReLU activation models. Taking the average value of three experimental results, it can be seen from the accuracy histogram that compared with other models, the algorithm in this paper has achieved the highest training and recognition accuracy in 12 subclasses (15 in total). The average accuracy is calculated for three categories: weather, location and driving time. The results show that the algorithm in this paper leads ReLU, ELU and LReLU by 8.58%, 7.94% and 16.55% respectively, as shown in TABLE II. Because every training of LReLU changes the super parameters of the activation function, the training is unstable[14-17].

Calculate the kappa coefficient on 15 sub categories for each model, which is an index that can reflect the classification performance of the model under the condition of unbalanced data. The closer the value is to 1, the better the performance is. It can be found that the recognition performance of the model in this paper is higher than that of other models. The data are shown in Table III.

TABLE II. Average accuracy of each model category

Model	Sigmoid	Tanh	ReLU	ELU	LReLU	DL
Correct recognition rate	60.84%	67.89%	75.22%	75.68%	67.21%	83.78%

TABLE III. Kappa score of each model

Model	Sigmoid	Tanh	ReLU	ELU	LReLU	DL
Correct recognition rate	66.56%	70.31%	77.15%	77.93%	72.50%	86.85%

The model in this paper is lower than the ReLU, ELU and ReLU models only in the three categories of snow, highway and night are 1.54%, 1.48%, 0.01%. Other categories have achieved the highest training recognition accuracy and the highest average accuracy. The average accuracy of ReLU is higher than that of LReLU, which reflects that LReLU is prone to oscillation and instability. Sigmoid and Tanh function

models are significantly different from ReLU model[18-23], so they are rarely used in deep networks. The experimental results show that the average accuracy of this model is 8.58% and 16.55% higher than that of ReLU and LReLU, which proves that this model can improve the recognition performance of deep learning model for road scene. In addition, by investigating the loss reduction of the three branch networks, it can also be found that the algorithm in this paper can effectively reduce the training loss of the model and have better convergence. The details are shown in Figure 7.

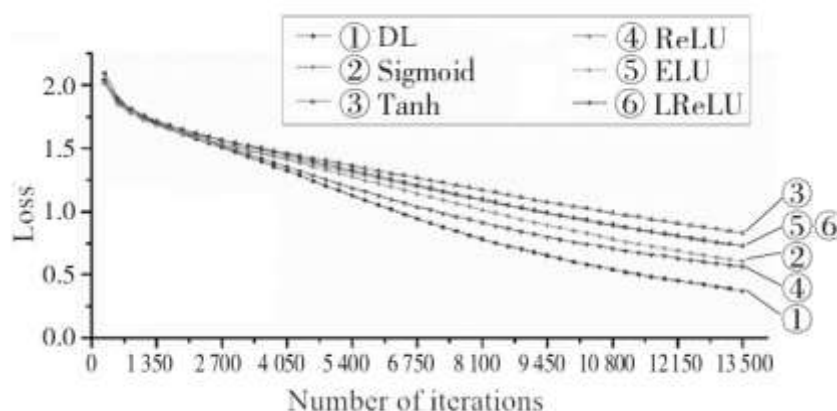


Fig 7: Training loss

VI. CONCLUSION

This paper proposes an improved activation function combined with ReLU and sigmoid activation function. The experiment on the road scene data set of the University of Berkeley shows that the average recognition accuracy of this model is improved by 8.58% and 16.55% compared with ReLU and LReLU models, which proves that this algorithm can improve the recognition performance of deep learning model. Compared with sigmoid and Tanh functions, the recognition accuracy of large road data sets is significantly improved, which overcomes the shortcomings that ReLU function cannot extract features in the negative half axis and LReLU is easy to oscillate. At the same time, there is still room to improve the recognition accuracy of some road scene categories. In the next stage, the main research work is to enrich the data set and optimize the network structure super parameters to further improve the recognition accuracy of various road scene information.

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