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Driver Fatigue Detection based on Multi-task Convolutional Neural Network

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Abstract

Fatigue detection technology has become an important detection technology for drivers during driving. Traditional face fatigue judgment and recognition based on machine vision cannot express the relationship between various fatigue features. Deep learning can explore the nonlinear relationship between driver fatigue and facial fatigue characteristics. Therefore, this paper proposes a multi-feature fusion vehicle driver fatigue detection algorithm based on convolutional neural network. First, use the Multi-task Convolutional Neural Network to locate key points on the face, and then extract the feature images of the eyes and mouth and locate the eyes; secondly, construct the eye and mouth data sets to complete the classification of eyes and mouth states Model training; finally, use the trained model to fuse the features extracted from the fatigue features of the eyes and mouth to detect driving fatigue. The experimental results show that the accuracy of the model reaches 94.7%.

Keywords

Multi-task Convolutional Neural Network; Fatigue Discrimination; Feature Fusion; Face Detection.

1. Introduction

In recent years, with the continuous improvement of living standards, the number of motor vehicles has increased year by year, and the number of deaths caused by traffic accidents has also increased. According to relevant surveys, driving fatigue is one of the important causes of traffic accidents. Therefore, in order to better avoid the loss of life and property caused by driving fatigue and improve driving safety, it is of great significance to develop a timely and effective driving fatigue detection method.

With the continuous development of artificial intelligence technology, many researchers have carried out research on driving fatigue detection based on deep learning. The current detection methods are roughly divided into three types: the first method is to perform detection according to the driving conditions of the vehicle. The second way is to monitor the physiological signals of the driver, mainly including EEG signals, ECG signals, and EMG signals. The third way is to perform detection based on the driver's facial features, including eye, mouth features, and head posture. This paper adopts the third method to realize the recognition of fatigue algorithm based on MTCNN.

2. Algorithm Principle

The overall flow of the fatigue detection algorithm used in this paper is shown in Figure 1.

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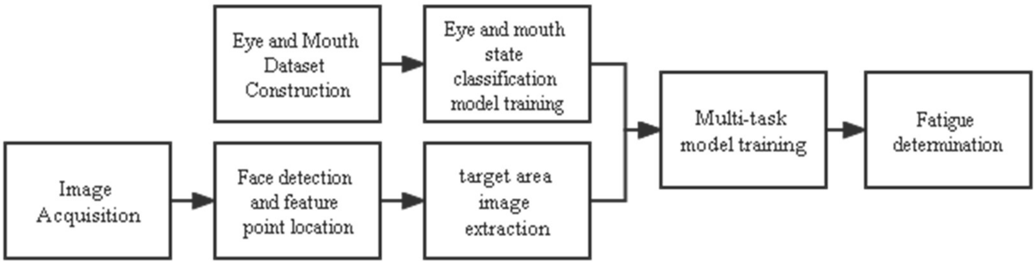

Figure 1. Flow chart of fatigue driving detection algorithm

2.1 CNN

CNN is the most representative model in deep learning, and it has high efficiency and accuracy when using CNN to process images with high dimensions and large amounts of data. The network structure of CNN mainly includes convolutional layer, pooling layer and FC layer.

(1) Convolution layer

The convolution layer is mainly responsible for feature extraction, convolution of the input data or feature map through the filter, and then outputting the feature map after the non-activation function. The convolution process expression is:

$$y = f(\sum_{i=1}^{n} x_i w_i + b_i)$$

Among them: w_i is the weight; b_i is the bias.

(2) pooling layer

The pooling strategies of the pooling layer mainly include max pooling, average pooling and random pooling. Pooling layers reduce the amount of data to be processed, thereby speeding up computation and preventing network overfitting. The pooling expression is:

$$x_i^l = f(\beta_i^l down(x_i^{l-1}) + b_i^l)$$

(3) fully connected layer

The fully connected layer is mainly responsible for mapping the high-level abstract feature representation extracted by multiple convolution and pooling operations to the sample label space, and its expression is:

$$h_{w,b}(x) = f(w^T x + b)$$

The training of the convolutional neural network adopts the error inverse propagation algorithm, which propagates the error of the real output and the calculated output in reverse step by step, and optimizes the weights and biases of the loss function of each network layer by the gradient descent method, so that the error reach the minimum. The loss function is defined as:

$$L(w,b) = \frac{1}{2n} \sum_{i=1}^{n} \left\| h_{w,b} - y \right\|_i^2$$

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Among them: n is the number of training samples; y is the output real value. The smaller the value of $L(w,b)$, the better the weights and biases obtained by the network training, and the better the performance of the model.

2.2 MTCNN

The MTCNN algorithm is based on deep learning to jointly detect face bounding boxes and feature points, mainly including three cascaded network structures of P-Net, R-Net, and O-Net.

(1) Proposal network:Obtain the candidate window and bounding box regression vector through a fully convolutional network, and use the bounding box regression vector to calibrate the candidate window, and use the non-maximum suppression algorithm to merge overlapping windows.

(2) Refine network:The candidate window obtained by P-Net is further screened, and a more accurate face candidate region is also obtained through the bounding box regression vector calibration and the NMS algorithm.

(3) Output network:Its function is similar to that of R-Net. It mainly screens the candidate area to obtain the final face position, and locates five face feature points on both sides of the eyes, nose, and corner of the mouth.

2.3 Fatigue Judgment and Multi-feature Fusion

When the driver is tired, the eyes will be closed for a long time and the frequency of yawning will be high. In order to detect the fatigue state more accurately, this paper combines the conditions of the eyes and the mouth to make a comprehensive judgment.

The PERCLOS method proposed by the Carnegie Mellon Institute is a more commonly used detection method when judging the fatigue state according to the facial features of a person. The formula looks like this:

$$P = \frac{N_c}{N_t} \times 100\%$$

Among them, P represents the time occupancy ratio of the eyes in the closed state within a certain period of time; N_c represents the number of frames in the closed state of the eyes within a certain period of time; N_t represents the total number of frames in the period of time. According to experience, when the calculated value is greater than or equal to 0.4, it means that the driver is in a fatigued state, otherwise it is a normal state.

When the driver is in a fatigued state, another characteristic is yawning, so whether the driver is fatigued can be judged by the opening and closing state and opening time of the mouth. However, in the detection process, the important interference factor of speaking should be excluded first. According to research, the time for a person to yawn is about 3 seconds, and the mouth is in a state of continuous opening and closing when speaking, so yawning can be determined through the improved MAR mechanism. Since the mouth is in overall motion during movement, and there are 8 feature points in the mouth area. Therefore, the internal coordinates of the lips are used for calculation, and the fatigue is judged by the value of the aspect ratio of the lips, MAR, as shown in the following formula.

$$MAR = \frac{\|p\|}{3\|p_1 - p_5\|}$$

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Authoritative studies have found that when the MAR value is greater than 0.9, it can be determined that the driver is in a state of fatigue.

In order to detect and determine the fatigue state more accurately, this paper combines the features of eye fatigue and mouth fatigue. If P is greater than or equal to 0.4, or MAR is greater than or equal to 0.9, the driver is in a fatigue state.

3. Experiment and Result Analysis

3.1 Lab Environment

The experimental environment in this paper is Raspberry Pi 4B, 8G memory, numpy version number is 1.16.5, opencv version number is 3.4.2.16, Keras version number is 2.3.1, tensorflow version number is 2.0.0, scikit_learn version number is 0.23 .2.

3.2 Experimental Results

100 face images were selected for testing, and the average accuracy was 94.7%. It can be seen from the experimental results that the method proposed in this paper has certain feasibility in terms of accuracy. In this paper, by simplifying the image features, it is possible to use a network with a simple structure to classify the state of the eyes and mouth.

3.3 Running Effect Display

In order to clearly show the operation effect, according to the PERCLOS fatigue judgment standard, this paper uses real-time video to test, and the test effect is shown in the figure below.

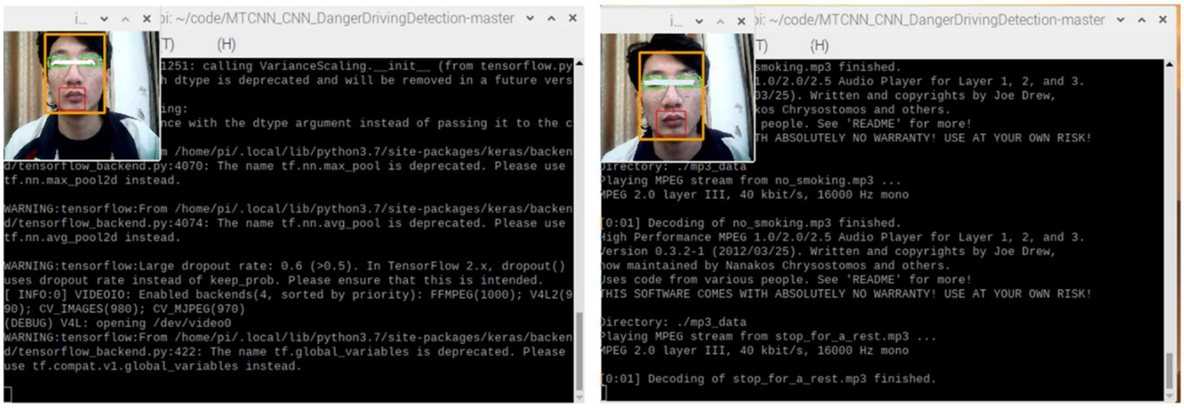

Figure 2. Fatigue test chart

The real-time performance of the fatigue detection method proposed in this paper is also extremely high, which can remind drivers of fatigue in time, and remind them to reduce the occurrence of traffic accidents.

4. Conclusion

In this paper, a driving fatigue detection method based on MTCNN is proposed. Through the introduction of the algorithm, the usefulness of multi-task convolutional neural network for actual driving fatigue detection is verified, and a certain theoretical foundation is laid for subsequent research. References.

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