Research on Facial Fatigue Detection of Drivers with Multi-feature Fusion

YE Yuxuan[1], ZHOU Xianchun[2], WANG Wenyan[2], YANG Chuanbin[2], ZOU Qingyu[1]

(1. *School of Electronic and Information Engineering*, *Nanjing University of Information Science and Technology, Nanjing 210044*; 2. *School of Artificial Intelligence* (*School of Future Technology*), *Nanjing University of Information Science and Technology*, *Nanjing 210044*)

Abstract: In order to solve the shortcomings of current fatigue detection methods such as low accuracy or poor real-time performance, a fatigue detection method based on multi-feature fusion is proposed. Firstly, the HOG face detection algorithm and KCF target tracking algorithm are integrated and deformable convolutional neural network is introduced to identify the state of extracted eyes and mouth, fast track the detected faces and extract continuous and stable target faces for more efficient extraction. Then the head pose algorithm is introduced to detect the driver's head in real time and obtain the driver's head state information. Finally, a multi-feature fusion fatigue detection method is proposed based on the state of the eyes, mouth and head. According to the experimental results, the proposed method can detect the driver's fatigue state in real time with high accuracy and good robustness compared with the current fatigue detection algorithms.

Keywords: HOG Face, Posture Detection, Deformable Convolution, Multi-feature Fusion, Fatigue Detection

1 Introduction

Fatigue driving is one of the main factors leading to car accidents. Therefore, the development of driver fatigue detection technology is crucial, which can effectively test whether a driver has fatigue driving and reduce the occurrence of car accidents. There are three main types of fatigue driving assistance systems on the market[1]: Fatigue detection based on vehicle condition, fatigue detection based on driver's physiological state and fatigue detection based on driver's facial characteristics. Li Zoujin et al. used sensors to obtain signals of steering wheel turning angles under actual driving conditions and used a binary classifier to determine whether the driver is currently fatigued or awake, but the method is negatively affected by various aspects such as different drivers' driving habits and actual road conditions[2]. Kaijie Guan et al. used glasses as a carrier with built-in sensors, and the driver wore the glasses while driving, and judged the driver's fatigue by detecting the characteristics of the eyes combined with the changing state of the driver's EEG signal, but the driver wearing the sensors would affect the state of driving, and it was difficult to promote it[3]. Shiqi Dai et al. trained by convolutional neural networks to identify classification patterns of eye opening and closing conditions, establish eye fatigue features, and determine the current fatigue condition of the driver based on the comprehensive mouth fatigue characteristics, but the fatigue detection algorithm based on deep learning, with more parameters and larger models, lost its timeliness in practical applications[4].

Research on the practical application of fatigue driving test technology is carried out. Combining traditional face detection algorithm with deep learning technology, a multi-feature fusion driver facial fatigue detection method is proposed. The main research contents are as follows.

(1) In order to reduce the running time of the detection algorithm, the fusion of HOG face detector and KCF target tracking algorithm is used to propose the HOG face detection algorithm based on kernel correlation filtering to detect and track the collected face information. In order to further improve the accuracy of the fatigue detection system, Dlib library in OpenCV is invoked to extract the key points of the driver's face.

(2) In order to increase the recognition accuracy of the detection algorithm, deformable convolutional neural network was introduced for state recognition of the extracted eyes and mouth. The head pose algorithm is introduced to detect the driver's head in real time, and the head pose prediction algorithm based on geometric correlation is used to evaluate the driver's head features by studying the change rule of human facial feature points.

(3) Finally, a multi-feature fusion fatigue detection method is proposed according to the state of the driver's eyes, mouth and head[5]. By testing the collected data sets, the accuracy of the fatigue detection system reaches more than 90%. By simulating the normal and fatigue state of the driver, the fatigue detection system designed in this paper can determine the driver's state in real time, and can also import video from the local to detect the driver's state.

2 Related Work

2.1 Face Detection

2.1.1 HOG Algorithm

Histogram of oriented gradient (HOG) [6] means that the gradient direction histogram of the local overall scope of the detected image is used to depict the characteristics of the target, so that the overall contour of the target can be depicted more correctly. One of the main features of HOG face detection algorithm is that after subdividing pixels into small cells, a one-dimensional ladder (or edge direction) histogram is calculated from each cell, and then the histogram is combined to form a feature descriptor. Since HOG implements the normalization operation on the local whole square unit of the image, the negative effects of various factors of light and deformation are greatly reduced.

2.1.2 KCF Tracking Algorithm

Kernel Correlation Filter (KCF) is a real-time correlation filter[7], which is faster than mainstream deep learning tracking algorithms. It obtains more samples by moving the frame on the sample, thus improving the recognition accuracy of the image, and realizes the optimization and acceleration of the method by using the periodic movement of the sampling points[8].

2.1.3 Extraction of Key Points on The Face

Face feature point localization refers to the localization of all organ locations in a face feature image using image processing, pattern recognition and other technical means. By selecting a face feature point analysis technique based on Dlib database[9], it is thus possible to quickly achieve the acquisition of key points of face features using Dlib database. In this paper, a KCF-based improved algorithm for HOG face detection is proposed, which can detect the driver's face in real time by calling the Dlib library[10] of OpenCV and labeling 68 key points of the face.

2.2 Head Posture Analysis

Head posture is the degree of deflection of the human head relative to the three-dimensional coordinates at a given moment[11]. In mathematical formulas, the amount of rotation in three-dimensional space has many expressions, the most common of which are quaternions, axis pinch angles, rotation matrices and their Euler angles. According to the three axes of Euler angles, the pinch angles of rotation around the X-Y-Z axes are generally defined as pitch, yaw, and roll angles, respectively. Euler's angle[12], which is the three diagonal parameters that determine the direction of motion of a rigid body in three-dimensional space, was first proposed and named by Lenhard Euler, as shown in Fig.1, with Euler's angle can represent the head posture.

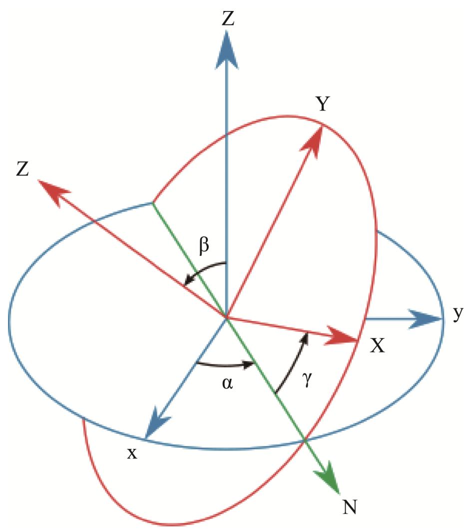


Fig.1 Euler Angle

3 Design of the Experimental Methods

3.1 Face Detection Algorithm Based on HOG

The selected unit range size is 8 × 8 pixels (n = 8), the orientation time region n is 9, the unit block size is 16 × 16 pixels (K = 4), and the sliding step L is 8. When the input image size is 128 × 128 pixels, then the HOG feature vector is generated.

1. Input the face training sample and the orientation coordinate system of the face in the sample, which represents the 4-dimensional position coordinates of the enclosing frame of the image. (top、left、width、height).

2. All sample images are scanned after pre-processing the images to obtain the characteristics of each image HOG.

3. The labeled face region is used as positive, and the region without face features is randomly selected from other regions as negative samples for SVM training, and the training is completed when the loss is lower than the set value of 0.01, indicating that the SVM has been designed and optimized, and the trained face detector model is provided.

The experiments integrate the HOG face algorithm with the kernel correlation filter tracking algorithm in order to detect the driver's face in real time and achieve more efficient extraction. This approach can reduce the frequency of face inspection, shorten the time consumed for inspection, and improve the robustness to driver face pose changes, occlusions. the KCF algorithm also incorporates HOG features and kernel methods to achieve good results in the accuracy of target tracking as well as kernel speed to meet the requirements of the designed fatigue detection method[13].

3.2 Deformable Convolutional Networks for Facial State Recognition

Considering the application and efficiency of the fatigue detection system, a fully convolutional neural network structure is used to introduce a deformable convolutional neural network in order to train a pattern for eye and mouth recognition with higher accuracy[14]. The convolutional kernel used can adjust its own shape according to the actual situation to better extract the features of the input image and improve the ability to adapt and generalize to unknown changes.

Due to the advantages of deformable convolution[15], networks using deformable convolution achieve good results on different tasks, but this still does not get rid of the drawback of needing to completely retrain the network, an algorithm is proposed to enhance the effectiveness of existing networks using deformable convolution, which upgrades the standard convolution in the network to deformable convolution and the network is upgraded in place, it does not degrade the results of the network and only a small amount of data fine-tuning is required to achieve better results than before.

The deformable convolution introduced in this paper is to improve on the CNN and replace part of the designed convolution from the computational layer to the deformable convolution layer, and finally the basic structure obtained contains input and output layers (Input), three convolutional layers (C), two downsampling layers (S), one deformable convolutional layer (DC), two fully connected layers (F), and input-output layer (Output). This is shown in Fig.2.

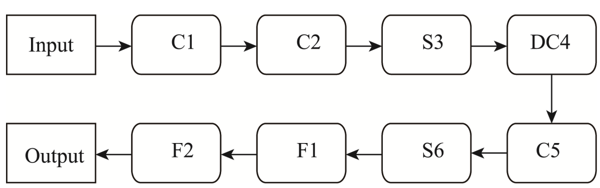


Fig.2 Network Structure of DC-CNN

3.3 Head Posture Estimation Algorithm Based on Geometric Approach

The coordinates of the driver's head are collected to describe the posture of the head by using the lateral, prone and rollover angles. The tilt angle is the prone motion of the head and prone motion, the roll angle is the driver's body activity, and the lateral angle is the body motion. The lateral angle in vehicle driving indicates the driver's front and rear directions during driving, while the tilt angle and roll angle indicate the head posture when the driver is fatigued[16]. The head posture is captured using the camera at the front of the seat, and the mode expression of the camera is shown in (1).

$$s\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} f_x & 0 & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} r_{11} & r_{12} & r_{13} & t_1 \\ r_{21} & r_{22} & r_{23} & t_2 \\ r_{31} & r_{32} & r_{33} & t_3 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix} \tag{1}$$

X, Y, Z are the 3D position coordinates in the world coordinate system. The scale factor, 2D coordinate system, 3D coordinate system and the internal reference matrix are the key parameters. The information collected by the camera allows a simple calculation of the plane vector so that R can be obtained. while the Eulerian angle is expressed by the rotation matrix method, and the result is shown in Equation (2).

$$\begin{aligned} R_x(\alpha) &= \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\alpha & \sin\alpha \\ 0 & -\sin\alpha & \cos\alpha \end{bmatrix} \\ R_y(\beta) &= \begin{bmatrix} \cos\beta & 0 & -\sin\beta \\ 0 & 1 & 0 \\ \sin\beta & 0 & \cos\beta \end{bmatrix} \\ R_z(\gamma) &= \begin{bmatrix} \cos\gamma & \sin\gamma & 0 \\ -\sin\gamma & \cos\gamma & 0 \\ 0 & 0 & 1 \end{bmatrix} \end{aligned} \tag{2}$$

Representing the rotation matrix as a sine and cosine matrix composed of Euler angles, as shown in Equation (3), it has been calculated using the camera model with nine main covariates and reaching the conjunction.

$$\left\{ \begin{aligned} &R = \begin{matrix} \cos\alpha\cos\beta & \cos\alpha\sin\beta\sin\gamma - \sin\alpha\cos\gamma & \cos\alpha\sin\beta\sin\gamma + \sin\alpha\cos\gamma \\ \cos\alpha\cos\beta & \sin\alpha\sin\beta\sin\gamma + \sin\alpha\sin\gamma & \sin\alpha\sin\beta\sin\gamma - \sin\alpha\sin\gamma \\ -\sin\beta & \sin\alpha\sin\beta & \cos\alpha\cos\beta \end{matrix} \\ &R = \begin{pmatrix} r_{11} & r_{12} & r_{13} \\ r_{21} & r_{22} & r_{23} \\ r_{31} & r_{32} & r_{33} \end{pmatrix} \end{aligned} \right\} \tag{3}$$

$$\begin{cases} \alpha = \arctan\left(\dfrac{r_{32}}{r_{33}}\right) \\ \beta = \arctan\left[\dfrac{-r_{31}}{\sqrt{r_{32}^2 + r_{33}^2}}\right] \\ \gamma = \arctan\left(\dfrac{r_{21}}{r_{11}}\right) \end{cases} \tag{4}$$

As described in (3), the Euler angle is derived from the mentioned rotation matrix parameter, and the expression of the Euler angle is (4). The posture signal is calculated in terms of the Euler angle, and it is possible to determine the actual collected driver head condition and whether the fatigue driving condition has been reached.

Fatigue driving can cause drivers to show a different state than normal driving, as evidenced by frequent head nodding or head deflection from side to side when dozing off. The change in head perspective can then be a criterion for determining whether a driver can drive fatigued. If the driver's head condition is checked abnormally in multiple frames, it can be determined that the driver has been driving fatigued and an effective warning is given to the driver. In the normal state, the driver's pitch angle variation range is generally 1°~7°, and in the fatigue state, the pitch angle range is generally 15°~30°. In the usual posture of the driver's head dynamics is not obvious, in the fatigue state, the direction of the Euler angle surface changes more, there is a certain degree of unpredictability, indicating that this is mostly abnormal state. In the usual posture, X (pitch angle) and Z (roll angle) are close to zero, so if the zero-degree pitch angle and zero-degree roll angle for the median point posture, the orientation offset of any one angle is greater than twenty percent, you can judge the driver's head in abnormal conditions.

3.4 Determination of Fatigue Status

3.4.1 PERCLOS

PERCLOS[17] is one of the most important indicators for the detection of driver fatigue and its value can be used to indicate whether the eyes are open or closed. the value of PRECLOS represents the proportion of time that the eyes are closed and is shown by equation (5). The EAR value was designed according to the PERCLOS principle and the characteristics of the eye. Set 0.3 as the threshold value of EAR, when it is less than the threshold value, the eye is judged to be in the closed state, otherwise the eye is judged to be in the open state.

$$f = \frac{c-b}{d-a}100\% \tag{5}$$

3.4.2 Blink Frequency

Blink Frequency[18] refers to the number of times an eye is opened or closed per unit of time. The average driver is very focused, blinking 10-15 times a minute. Driving for a long time can make drivers tired, causing them to blink no more than 10 times a minute. Therefore, by detecting the number of blinks per unit time, the driver can reflect whether there is fatigue state. The calculation formula is shown in (6) below, where n is the number of blinks, t is the time, and N is the total number of frames.

$$BlinkFreq = \frac{n}{t*N} \tag{6}$$

3.4.3 Yawn

The determination of fatigue driving also enables the detection of oral conditions. Based on the driver's mouth shape, you can tell whether he is normal, talking or yawning. When a driver is driving, his mouth is closed and slit, while when he yawns, his mouth is open. Drivers often yawn frequently when they are tired of driving. When a driver is yawning, his or her mouth should be open wide. And yawning is a long-term process, so once the detection system monitors that the driver's mouth is in a normally open condition and remains open for a period of time, it is determined that the driver is yawning.

4 Experiment and Result

4.1 Experimental Environment

The hardware test environment is i7-8750H quad-core 2.2GHz, graphics card GeForce GTX 1050Ti, memory 12GB, operating system Windows11, the software used is VSCode, Python3.7.

4.2 Comparison of Face Detection Algorithms

Firstly, the face detection algorithms of HOG, Adaboost and MTCNN are analyzed. In order to shorten the execution time of the algorithm, the face detection algorithm of HOG and the target tracking algorithm of KCF are integrated, and then the speed, accuracy and other aspects of the three algorithms are analyzed respectively. By comparing three FACE algorithms, HOG, Adaboost and MTCNN, two data sets of Face-Scrub and WIDER FACE are tested, and the experimental results are shown in Table 1.

Table 1 Comparison of Face Detection Algorithms

Algorithm	FaceScrub (%)	Wider Face (%)	Time(ms)
Adaboost	86.7	89.1	25.2
MTCNN	95.7	96.6	42.4
HOG+KCF	95.1	94.5	33.5

From the point of view of accuracy, MTCNN and HOG+KCF are better than Adaboost algorithm. From the point of view of time, Adaboost and HOG+KCF are the two traditional algorithms. Under comprehensive consideration, the HOG fusion algorithm based on kernel correlation filtering is selected to detect the driver's face.

4.3 Extraction of Key Points on the Face

The face detection improvement algorithm based on KCF is proposed, and then the Dlib library is called for facial keypoint recognition. If the driver's head is turned slightly for personal reasons, the driver's face can still be detected dynamically in real time and the 68 key points of the face can be accurately located, and the results are shown in Fig.3.

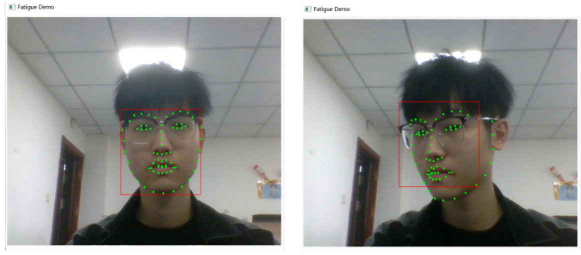


Fig.3 Face Feature Point Positioning Effect

4.4 Head Posture Detection

By calling the Dlib library, 68 feature points of the face are collected dynamically, marked with the internal and external parameters of the camera head in advance, the Angle matrix is calculated by the camera head, and the Euler Angle is calculated by the Angle equation, so as to complete the estimation method of real-time automatic collection of the driver's head posture. The experimental results are shown in Fig.4.

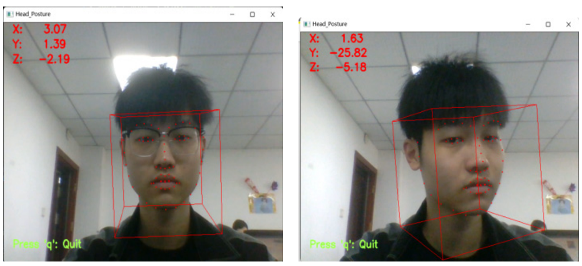


Fig.4 Head Posture Detection Diagram

4.5 Eye and Mouth Condition Detection

4.5.1 Eye and Mouth Datasets

In order to construct the eye datasets and mouth datasets to improve the accuracy of face state recognition, the proposed new method selects the CEW eye datasets, YAWDD yawning datasets which are publicly available online and the homemade datasets. There are 8500 images, including 5500 images for eye samples and 3000 images for mouth samples. To enhance the detection results, the images were normalized to 32x32 pixels for network training, with a total of 10,000 iterations. Some of the collected eye samples are shown in Fig.5, and some of the mouth samples are shown in Fig.6.

Fig.5 Partial Eye Sample

Fig.6 Partial Mouth Sample

4.5.2 Eye and Mouth Detection

In order to verify whether the proposed method of eye and mouth state can achieve the expected effect, DC-CNN is used to test and verify the trained data set. Table 2 shows the test results of eye state and Table 3 shows the test results of mouth state.

Table 2 Eye Condition Test Results

Condition	Number of Samples	Number of Errors	Accuracy
Open	2500	88	96.48%
Close	1500	65	95.67%

Table 3 Mouth Condition Test Results

Condition	Number of Samples	Number of Errors	Accuracy
Open	750	39	95.47%
Close	500	24	95.18%

From the experiments, it can be seen that the DC-CNN algorithm has a high accuracy rate for eye and mouth recognition and can meet the requirements of the fatigue detection system. As shown in Table 4, the eye state recognition based on deformable convolutional neural network is better than the other two algorithms.

Table 4 Results of Different Algorithms for Eye State Recognition

Algorithm	Open-eye Accuracy	Close-eye Accuracy
DC-CNN	96.48%	95.67%
Adaboost	85.57%	86.34%
MTCNN	94.56%	93.81%

5 Multi-feature Fusion for Fatigue Detection

First of all, the HOG detection algorithm based on KCF is used to detect the face of each preprocessed frame image, and then the eyes and mouth areas are obtained through the driver key points by calling the Dlib library in OpenCV. Then the deformable convolutional neural network was used to detect the eye state and mouth state of each frame, and the driver's head was detected in real time through the head attitude algorithm. Finally, according to the detected state of the eyes, mouth and head, statistics whether the fatigue state, once the calculation exceeds the set normal threshold, the system will display "SLEEP" and remind the driver in time.

EAR is used to make statistics on the state of eye closure, BlinkFreq is used to make statistics on whether the driver blinked, MAR is used to make statistics on whether the mouth yawned, and head posture algorithm is used to make statistics on the state of head. The CEW Eye dataset and YAWDD video dataset are used to test the performance of the fatigue detection algorithm. The threshold of fatigue state is determined by EAR exceeding 0.3, blink rate exceeding 20 per minute, yawn rate exceeding 3 and nod frequency exceeding 2 times. At the same time, the system can detect whether the driver is off duty. If the driver's face cannot be detected in the designated area for 5 consecutive seconds, it will remind the driver to "staff off duty". By judging the state of eyes, mouth and head, fatigue test is carried out according to the set threshold to realize the judgment of driver fatigue.

In order to verify the accuracy of the proposed new method of fatigue detection, 10 videos were made from the experimentalists to simulate the driving states of drivers, including non-fatigue driving states and fatigue driving states. According to the state classifier of the corresponding experimenter, the eye state, mouth state and head state can be discriminated. Finally, the EAR, blinking frequency and yawning frequency of the corresponding test person in this video are calculated respectively, and if the tested indexes exceed the set threshold, fatigue will be determined, and the experimental results are shown in Table 5. From the table, it can be seen that the accuracy of the detection of fatigue driving in the 10 videos is more than 90%.

Through face detection and tracking, eye and mouth state extraction, eye and mouth state recognition work, realistic statistics of multiple testers. Simulate the normal state of the driver driving as shown in Fig.7(a), fatigue state as shown in Fig.7(b), reach the set fatigue threshold, fatigue detection system will make a warning to remind the driver.

For some reasons, drivers are faced with wearing a mask when driving. Although wearing a mask cannot detect the mouth, but through the eyes and head detection can still detect the driver status, through the blink and EAR value, the number of blinks per minute three values for driver fatigue determination, the driver wearing a mask of normal and fatigue state is shown in Fig.8.

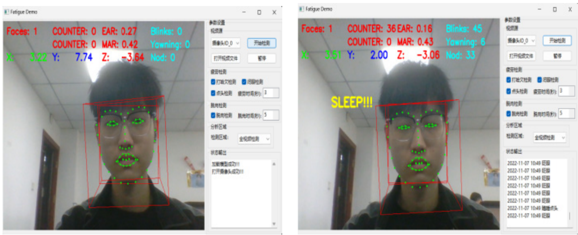
This paper designs the fatigue detection system not only to detect the driver's status in real time, but also to detect the driver's status in the video by importing the video. The detection results are shown in Fig.9.

When the driver's face is out of the range of the fatigue detection system designed in this paper when driving, if the time exceeds 5 seconds continuously, this time the detection system will remind the driver off duty, and will alert the driver to the early warning, the detection results are shown in Fig.10.

Finally, the fatigue detection system was tested on the collected YAWDD dataset with an accuracy of 94.36%. The system was tested and achieved the expected design goal and met the requirements of practical applications. The experimental results show that the designed fatigue detection system has good superiority and can accurately determine the fatigue status of drivers. Compared with the traditional fatigue detection method of Adaboost and the fatigue detection method of HOG+SVM, the multi-feature fusion driver

Table 5 Sample Fatigue Test

No.	EAR	Blink	Yawn	Nod	Test Status	Actual Status	Result
1	0.58	19	6	6	Fatigue	Fatigue	√
2	0.21	10	0	1	Normal	Normal	√
3	0.52	55	4	3	Fatigue	Fatigue	√
4	0.44	24	3	4	Fatigue	Fatigue	√
5	0.37	20	0	2	Fatigue	Normal	×
6	0.48	28	2	4	Fatigue	Fatigue	√
7	0.22	16	0	0	Normal	Normal	√
8	0.33	23	5	2	Fatigue	Fatigue	√
9	0.55	21	6	5	Fatigue	Fatigue	√
10	0.24	12	0	0	Normal	Normal	√



(a) Normal State Result (b) Fatigue State Result

Fig.7 Simulated Driver Status Detection Diagram

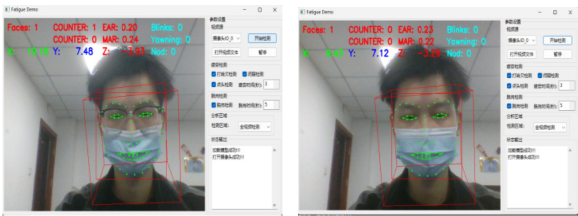
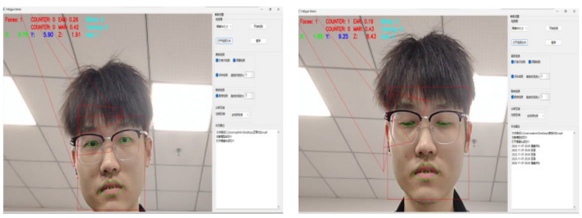


Fig.8 Simulated Driver Wearing a Mask



(a) Normal State Result (b) Fatigue State Result

Fig.9 Simulated Driver Status in Video

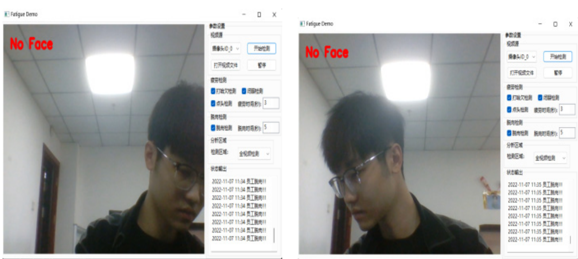


Fig.10 Off Duty Detection

facial fatigue detection method proposed in this paper has better timeliness and accuracy than the above two methods. Based on time and efficiency as well as practical applicability, compared with the traditional HOG+CNN fatigue detection method, the fatigue detection system proposed in this paper incorporates the KCF tracking algorithm to play an algorithmic acceleration role in face detection. Compared with the MTCNN+CNN algorithm, the variable convolutional neural network is introduced to increase the accuracy of the algorithm. It can be seen that, under normal hardware conditions, the fatigue detection system proposed in this paper improves the accuracy of the fatigue driving detection algorithm, has better real-time performance, and meets the requirements of the fatigue driving detection system, and the comparison results are shown in Table 6.

Table 6 Comparison of Different Algorithms

Method	Accuracy (%)	Time (ms)
Adaboost+SVM	89.28	48.1
HOG+SVM	91.85	52.5
MTCNN+CNN	94.75	74.7
HOG+CNN	93.60	64.2
Multi-Feature Fusion	94.36	55.7

6 Conclusion

In this paper, a KCF based HOG face detection algorithm is proposed to detect and track the collected faces, so as to reduce the time complexity of the algorithm. Then, deformable convolutional neural network was introduced to recognize the extracted eyes and mouth. The proposed deformable convolution operation is an extension of the standard convolution operation. Additional standard convolution operations are used to introduce the spatial shift of the values on the grid points compared with the standard convolution operation, which is used to change the position of the uniform grid sampling, so that the convolution operation can learn the free deformation information. The head attitude algorithm is introduced to detect the driver's head in real time, and the head attitude estimation algorithm based on geometric relation is used to judge the head attitude. Finally, according to the special state of eyes and mouth, some new detection methods are provided to integrate with facial features, and set the fatigue detection threshold. Through CEW and YAWDD data sets, the accuracy of fatigue detection is more than 94%. Compared with the current fatigue monitoring algorithm, the new algorithm can monitor driver fatigue in a more real-time manner and has great accuracy.

Compared with the traditional methods, the accuracy of the fatigue detection system designed in this paper is significantly improved by combining the traditional calculation and the in-depth practice of the driver fatigue test. Compared with the deep learning method, the fatigue detection system designed in this paper does not require higher hardware, and the time is shorter, achieving good effectiveness.

References

[1] WANG X Y, HAN T T, SHANG X D. (2021). Driver Fatigue State Detection Method in Dense Connected Network. Journal of Beijing University of Posts and Telecommunications. 44(01). pp. 52-58.

[2] YAN Y, YUAN H Z, YANG X L, LIU G, GUO Z Y, WANG L. (2021). Relationship Model between Monotonous Road Environment and Driver Fatigue Based on Multi-Source Data. China Journal of Highway and Transport. 34(05). pp. 156-167.

[3] WANG H T, YIN H J, CHEN C Q. (2022). Anastasios Bezerianos. Review of Driver Fatigue Detection Based on EEG. Journal of Huazhong University of Science and Technology (Natural Science Edition). 50(11). pp. 54-65+78.

[4] WANG J M, FAN Y Y, LI Z H. (2022). Texture Image Recognition Based on Deep Convolutional Neural Network and Transfer Learning. Journal of Computer Aided Design and Computer Graphics. 34(05). pp. 701-710.

[5] XIANG J W, WANG W. (2022). Facial Attribute Editing Method Based on Saliency Target Detection Network. Foreign Electronic Measurement Technology. 41(05). pp. 1-8.

[6] HU M, TEN W D, WANG X H, XU L F, YANG J. (2018). Facial Expression Recognition Based on Local Texture and Shape Features. Journal of Electronics and Information Technology. 40(06). pp. 1338-1344.

[7] GUO L. (2018). Multi-scale target Tracking Based on Kernel Correlation Filter. Journal of Electronic Measurement and Instrumentation.32(04). pp. 74-79.

[8] Henriques J F, Caseiro R, Martins P, et al. (2014). High-speed tracking with kernelized correlation filters. IEEE transactions on pattern analysis and machine intelligence. 37(3). pp. 583-596.

[9] LIU G D, DONG M K, ZHANG S W, XU L Y, ZHOU G, CAI J. (2021). Fatigue Classification of Surface EMG Signal Based on KPCA-SVM. Journal of Electronic Measurement and Instrumentation. 35(10). pp. 1-8.

[10] CHENG X H, DA F P, DENG X. (2018). 3D Face Feature Point Localization from Coarse to Fine Based on Key Points [J]. Journal of instrumentation. 39(10). pp. 256-264.

[11] LI R, CAI B, LIU L, WANG X. (2016). Driver's Eye State Recognition Based on Model, Journal of instrumentation. 37(01). pp. 84-191.

[12] YU R Y, LIN F Y, GAO N W, LI J. (2021). Prediction Model of Ride Demand Based on Deformable Convolution Space-time Network. Journal of Software. 32(12). pp. 3839-3851.

[13] YU C C, SA L B, MA X Q, CHEN X X, ZHAO X. (2020). Small Sample Zero Device Surface Defect Detection Based on Metric Learning. Journal of instrumentation. 41(07). pp. 214-223.

[14] YU J L, ZHANG Y. (2021). A Driver Warning Method Based on Multi-factor Fusion [J]. Electronic measurement technology. 44(11). pp. 103-108.

[15] ZHANG C T, SONG Z W, WANG Y, NIAN S P. (2016) Robot Working Point Pose Calibration Method Based on Space Grid. Journal of Zhejiang University (Engineering Science). 50(10). pp. 1980-1986

[16] BAI Z H, LIU L, JIAO Y H, CAO S. (2016). Multi-feature Fusion Driver Fatigue Detection Method Based on ASM [J]. Journal of electronic measurement and instruments. 30(12). pp. 1877-1883.

[17] ZHENG R H, NAN R Y, LI S X, WANG X Z, CHEN M X. (2021). Eye Feature Segmentation Method Based on lightweight network. Transactions of Beijing Institute of Technology. 41(09). pp. 970-976.

[18] SUN Y X, WANG S Z. (2021). Motion Evaluation in Virtual Reality Based on Eye Tracking. Electronic measurement technology. 44(18). pp. 24-30.

Author Biographies

YE Yuxuan is a M.Sc. candidate at Nanjing University of Information Science and Technology. His research interest includes digital image processing.

E-mail: 202212490130@nuist.edu.cn

ZHOU Xianchun (**corresponding author**), Ph.D., professor and M.Sc. supervisor at Nanjing University of Information Science and Technology, senior member of Chinese Society of Electronics, and member of Chinese Society of Artificial Intelligence. His main research interests include image processing and pattern recognition.

E-mail: zhouxc2008@163.com