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Design of Driver Fatigue Detection Early Warning System Based on Facial Multi-feature Fusion

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Abstract **—In this paper, a driver fatigue warning system based on facial multi-feature fusion is designed to monitor real-time fatigue by fusing features such as eye closure, mouth opening and head posture, combined with deep learning algorithms. The system uses a high-definition camera to capture images, and locates and recognizes key facial features by convolutional neural network (CNN) to calculate fatigue indicators such as PERCLOS and MAR. When the fatigue signal reaches a preset threshold, the system triggers an alert to remind the driver. Experimental results show that the system excels in fatigue detection accuracy and real-time performance, and can effectively improve driving safety.**

Keywords-driver fatigue detection; facial multi-feature fusion; deep learning

I. Introduction

As the number of automobiles increases dramatically, traffic accidents caused by driver fatigue have become one of the main causes of traffic safety problems worldwide. According to statistics, major traffic accidents caused by fatigue driving account for about 20% to 30% of global traffic accidents. Under the state of fatigue, the driver's alertness, judgment and reaction speed are significantly reduced, and it is very easy to cause collision accidents, especially in the highway, long-distance driving and night driving and other situations, the risk of driver fatigue is more prominent [1]. Such accidents not only cause casualties, but also result in huge economic losses and social impact.

Traditional fatigue detection methods, such as those based on physiological signals (e.g., EEG, heart rate monitoring) [2] or behavioral characteristics (e.g., steering wheel micro-motion, throttle control) [3], although they perform well in a laboratory environment, are difficult to be widely used in real driving environments due to the expensive equipment [4], inconvenience of wearing them, and interference to the driver. Meanwhile, behavioral feature-based detection methods have a certain degree of latency and are unable to detect fatigue in a timely and effective manner, especially when the fatigue level increases rapidly in a short period of time, which is a more prominent defect.

This study plans to construct a fatigue detection model by fusing multiple facial features (eye closure, mouth opening, head posture, etc.) [5] and utilizing machine learning algorithms such as deep convolutional neural networks (CNNs) [6]. The model analyzes the facial video stream captured by the camera in real time and determines the driver's fatigue level by evaluating fatigue-related feature parameters and comparing them with a set threshold. In this way, the system is able to issue timely fatigue warnings without interfering with the driver, thus reducing the risk of accidents caused by fatigue driving, and providing technical support for improving road traffic safety.

II. Objectives

In this study, a driver fatigue warning system based on facial multi-feature fusion is designed. By integrating multi-dimensional facial features such as eye, mouth and head posture, deep learning algorithm is used to realize accurate detection and real-time warning of driver fatigue state. The system uses a high-definition camera for non-contact image acquisition to ensure continuous monitoring of driver 's facial feature changes. Through advanced image processing technology and convolutional neural network (CNN), the system can extract and analyze facial key point information and calculate fatigue-related indicators, such as eye closure time ratio (PERCLOS) and mouth aspect ratio (MAR) [7], to accurately determine the degree of fatigue. When the system detects that the fatigue signal exceeds the set threshold, the alarm is triggered in time to remind the driver to take corresponding measures. The ultimate goal of the research is to design (1) a low-cost, non-invasive; (2) a real-time and efficient fatigue state detection; and (3) an optimized detection accuracy for complex driving environments, such as different lighting conditions. The fatigue driving detection system is designed to improve the accuracy and real-time performance of driver fatigue detection and provide technical support for reducing traffic accidents caused by fatigue driving.

III. System Design

A. System architecture design

The system architecture consists of five modules: basic environment, development environment, image acquisition and processing module, data monitoring module and early warning display module (As shown in Figure 1).

1) Basic environment: It covers the hardware equipment required by the system, including high-definition camera, image processor and computing platform, to ensure the smooth operation and efficient performance of the system. These devices are connected through interfaces to form a stable data acquisition environment.

2) Development environment: The PyTorch deep learning framework is mainly used to support the training and deployment of models. By constructing a convolutional neural network (CNN), the system can efficiently process facial feature extraction and fatigue state analysis.

3) Image acquisition and processing module: real-time access to the driver 's face image, and the use of image enhancement techniques (such as histogram equalization and noise removal algorithm) to improve image quality, to ensure the accuracy of the data. The module also realizes the positioning and tracking of facial key points, which provides an accurate basis for subsequent analysis.

4) Data monitoring module: real-time analysis of facial features, calculation of key fatigue indicators (such as PERCLOS and MAR). Based on machine learning algorithm, this module continuously optimizes the detection model and improves the accuracy of fatigue state judgment.

5) Early warning display module: when the fatigue index is detected to exceed the set threshold, the alarm system is triggered. The module uses a combination of sound and visual alarms to ensure that drivers can receive reminders in a timely manner, so as to take the necessary safety measures.

Through the collaborative work of the above five modules, the system can achieve efficient and real-time fatigue monitoring and early warning under the premise of ensuring driver safety, and promote the development of intelligent traffic safety technology.

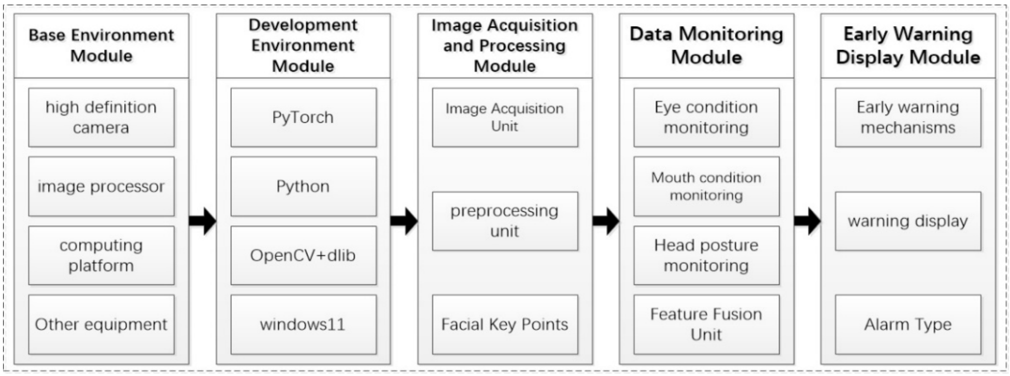

Fig. 1 System architecture diagram

B. *Image acquisition and processing module*

This module is one of the core of the system, which is responsible for collecting the driver's facial image in real time through the high-definition camera. To improve the robustness of the system, a variety of image preprocessing techniques are integrated, including illumination compensation, noise removal and image enhancement, to ensure that facial features can be clearly captured under various illumination conditions. Specifically, illumination compensation technology improves image contrast by adaptive histogram equalization (CLAHE), while noise removal uses a combination of Gaussian filtering and median filtering to reduce image interference [8].

The preprocessed image will be input into the deep learning model to extract key facial feature points, including eyes, mouth and head posture. In order to ensure the detection accuracy and real-time performance, this module uses convolutional neural network (CNN) technology, combined with image pyramid and multi-scale feature extraction strategy, to quickly and accurately identify and locate these key features.

In addition, this module also realizes dynamic facial tracking, and monitors the changes of facial features in video sequences by optical flow method to adapt to the driver 's natural movements during driving. This technology not only improves the stability of facial feature detection, but also provides a more reliable data basis for subsequent fatigue state analysis (As shown in Figure 2).

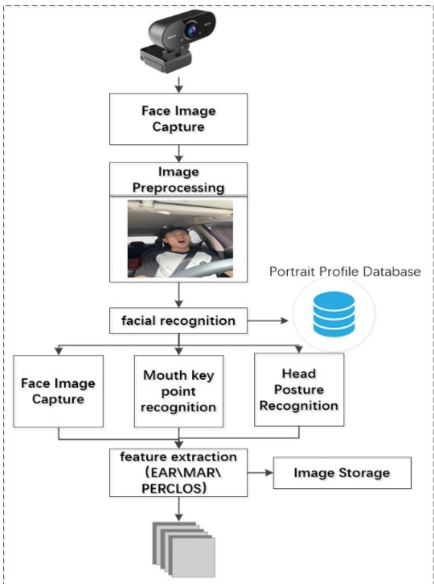

Fig. 2 Image acquisition and processing module

C. *Fatigue detection algorithm design*

The fatigue detection algorithm is the technical core of the system. It mainly identifies the driver 's fatigue state by analyzing the characteristics of the eyes and mouth combined with the head posture. The algorithm is based on convolutional neural network (CNN), which can effectively extract facial features and calculate key indicators [9], such as eye closure ratio (EAR), eye closure time ratio (PERCLOS) and mouth opening ratio (MAR). High-precision real-time fatigue detection is achieved through offline training and online testing.

In the offline training phase, the model is optimized using a large amount of labeled data to improve the accuracy of feature extraction. Specifically, data augmentation techniques (such as rotation, translation, and scaling) are used to increase the diversity of training samples, thereby enhancing the generalization ability of the model. The back propagation algorithm is used to optimize the network parameters, which makes the feature extraction more accurate and improves the overall performance of the system.

During online detection, the system updates PERCLOS, MAR and other indicators in real time to dynamically evaluate the driver 's fatigue state. To cope with the complex driving environment, the algorithm introduces a time series analysis method to monitor the fatigue trend through historical data to ensure the stability of the detection results. When the fatigue feature is detected to exceed the set threshold, the system will automatically determine that the driver is in a fatigue state, and immediately trigger the alarm mechanism, including sound and light prompts, to ensure that the driver receives timely feedback [10].

In addition, the algorithm also supports adaptive learning, which can continuously adjust the parameters according to the feedback in actual use to adapt to different driving environments and individual differences. This design not only ensures high-precision fatigue detection, but also enhances the adaptability of the system and provides reliable technical support for improving road safety. Through this innovative algorithm, the system realizes accurate and real-time driver fatigue state monitoring, and promotes the development of intelligent transportation technology.

D. *Real-time monitoring and early warning mechanism*

The module is responsible for continuously monitoring the driver's fatigue state and responding in time (As shown in Figure 3). The system calculates the key indicators, including PERCLOS, EAR and MAR, in real time through the facial feature data obtained by the image acquisition and processing module. These indicators can accurately reflect the driver 's fatigue level and provide a basis for subsequent judgment.

According to the preset safety threshold, the system automatically evaluates the driver's fatigue state. When the fatigue signal is detected to reach or exceed the set threshold, the early warning mechanism will be started immediately. The system uses a variety of alarm forms such as sound and vibration to ensure that drivers can be aware of potential dangers in a timely manner, so as to take the necessary measures to prevent accidents.

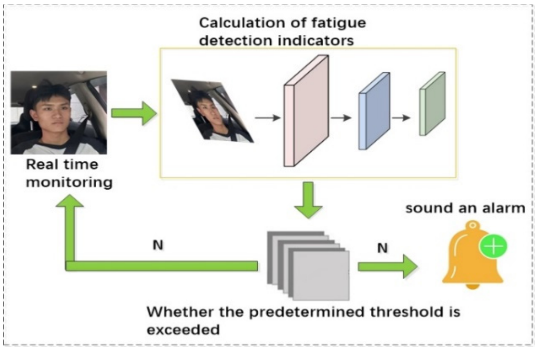

Fig.3 Implementation of monitoring

To improve the accuracy and timeliness of early warning, the system will perform multiple verifications on the fatigue signal before triggering the alarm. This process introduces sliding window technology to analyze the index changes in the past period of time in real time, thereby reducing the false alarm rate. In addition, the system design ensures that the early warning response speed is not less than several hundred milliseconds, ensuring real-time and reliability.

To further enhance the intelligence of the system, the early warning mechanism also integrates machine learning algorithms, which can be dynamically adjusted according to the driver's historical behavior data. This adaptive learning function enables the system to optimize the alarm threshold according to the individual differences of different drivers, thereby improving the pertinence and effectiveness of early warning.

Through the design of this module, the system realizes efficient and accurate fatigue monitoring and early warning, significantly improves driving safety, and lays a solid foundation for the future development of intelligent transportation system.

IV. EXPERIMENTAL DESIGN

A. *Experimental settings*

To verify the effectiveness of the system, the experimental settings include data acquisition, test environment configuration and evaluation criteria. The experiment was carried out in a simulated driving environment, and the driver 's facial images were collected in real time using a high-definition camera. Data acquisition includes images under different lighting conditions to ensure the robustness of the system. The test environment simulates long-term driving conditions, including normal driving and fatigue driving, to test the accuracy and response speed of the system. The evaluation criteria include the detection accuracy, real-time performance and false alarm rate of the system.

The experiments are performed on a high-performance computing server for model training, using Tesla P100 GPUs with powerful computational capabilities to support complex image processing and deep learning tasks (As shown in table 1). The system is configured with 128GB of RAM to provide sufficient storage space for efficient data processing and model running. Windows 11 is chosen as the operating system to ensure compatibility and stability with various applications. Meanwhile, the development environment is based on Pycharm and developed using the Python programming language, which facilitates code writing, debugging and maintenance. Such a combination of hardware and software can meet the high requirements of real-time, accuracy and stability of the fatigue detection system, and ensure the system to operate efficiently and reliably in different scenarios.

Table 1. System Development Environment

Development environment	Name of development environment
operating system	Windows11
CPU	Intel(R) Xeon(R) CPU E5-2630 v4
Memory space	128G
GPU	Tesla P100
Development Platform	Pycharm
Deep Learning Framework	Pytorch 1.12
Programming language	Python3.7.13

This study uses a self-constructed driver fatigue detection dataset, which contains 3000 video samples consisting of driver facial videos captured in multiple driving scenarios. The dataset is divided into 2500 training set samples and 500 test set samples to ensure the generalization ability of the model in different states.

All data were normalized and labeled with facial features in the preprocessing stage. First, the facial regions in each video are detected and cropped by a face detection algorithm. Next, key facial features such as eyes, mouth, and head pose are accurately localized using a keypoint detection algorithm. In addition, in order to ensure the robustness of the model, the dataset was subjected to data enhancement processes, including random rotation, flipping, brightness adjustment, and other operations, to simulate a variety of different driving environments.

B. Data acquisition and preprocessing

In the experiment, the driver 's facial images were collected through a high-definition camera, and the data included eye, mouth and head postures. In order to ensure the accuracy and real-time performance of the driver fatigue detection system, we chose a high-performance camera device for the acquisition of facial features. The camera used is a Basler ace series camera, model Basler acA1300-60gc. The camera has the following features:

1)High resolution and frame rate: the camera's combination of resolution and frame rate is ideally suited for real-time fatigue detection, enabling continuous acquisition of high-quality video in high-speed in-vehicle environments, providing sufficient information for input to deep learning models.

2)Superior Light Adaptability: As fatigue detection systems need to operate in varying light conditions, the Basler camera's automatic exposure control and highly sensitive sensor ensure that image quality is not compromised by ambient light, thus improving the stability and reliability of the detection.

3)Industrial-grade stability: Basler ace series cameras have industrial-grade stability, which can maintain efficient operation in high temperatures, vibration and other complex vehicle environments to ensure the system's stable operation for a long time.

4)Compatibility and scalability: Basler cameras support a variety of image processing interfaces and data output formats, enabling seamless integration with our existing computing platforms, and are highly scalable for future system upgrades and improvements.

The collected data is preprocessed, including illumination correction, image denoising and facial feature alignment. The preprocessing step ensures consistent image quality and provides accurate data for subsequent feature extraction and analysis (As shown in figure 4). The data sets used in the experiment cover different driving states, such as waking, fatigue and extreme fatigue, to verify the performance of the system in various states.

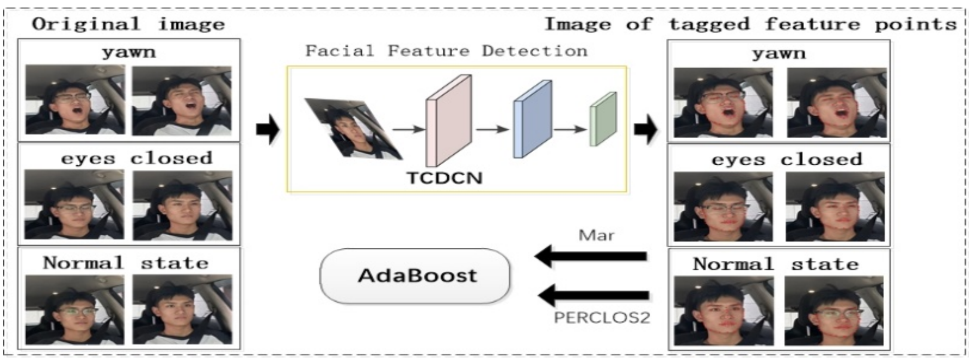

Fig.4 Experimental data processing flow

C. Analysis of experimental results

The experimental results are analyzed by comparing the fatigue state detected by the system with the real situation, as shown in table 2. The main evaluation indexes include detection accuracy, false alarm rate and response time. The accuracy rate is calculated by the ratio of true positive and true negative, and the false alarm rate is calculated by the frequency of false alarms. The experimental data show that the accuracy of the system under normal and fatigue driving conditions is more than 91%, and the false alarm rate is less than 5%. The response time of the system is at the millisecond level, which meets the requirements of real-time early warning.

Table 2. Analysis of experimental results

Driving state	Detection accuracy	False positive rate	Response time(ms)
wakefulness	93.2%	3.2%	143
fatigue	91.7%	4.7%	122
A state of extreme fatigue	95.1%	1.2%	118

D. Results discussion and optimization

Through the analysis of the experimental results, the system shows higher accuracy and lower false alarm rate under different driving conditions, but there is still room for further optimization. The false alarm rate may be related to illumination conditions, facial occlusion or algorithm parameter settings. Future optimization directions include improving image preprocessing algorithms, optimizing feature extraction models, and adjusting threshold settings to improve the robustness of the system in complex environments. In addition, increasing the diversity of test data sets also helps to further verify the effectiveness and stability of the system.

V. Conclusions

This study designed and implemented a driver fatigue warning system based on facial multi-feature fusion. The system uses a high-definition camera to collect facial images in real time. The system uses a convolutional neural network (CNN) to extract features from the eyes, mouth and head postures, and accurately calculates fatigue indicators, such as PERCLOS and EAR. The experimental results show that the system has high accuracy (more than 91%) and low false alarm rate (less than 5%) in detecting fatigue state, which can effectively identify the driver's fatigue degree and trigger early warning in real time. This shows that the designed system has good practicability and reliability, and can significantly improve driving safety.

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