Driver Fatigue Detection Based on Facial Recognition

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Abstract. Fatigue driving poses a significant threat to road safety, and monitoring driver alertness is essential for preventing accidents. This paper explores fatigue driving monitoring technology using facial recognition, which relies on non-contact visual analysis to detect fatigue based on key facial features such as eyelid closure, mouth movements, and head posture. This approach outperforms traditional methods such as physiological signal monitoring and vehicle behavior analysis, offering advantages in non-invasiveness, real-time detection, and improved accuracy in fatigue detection. Unlike physiological signal-based systems, which require invasive sensors, and vehicle behavior analysis that often suffers from latency, facial recognition technology can deliver timely alerts with high precision. Although significant progress has been made, challenges such as environmental interference and individual adaptability persist. Future advancements should focus on lightweight algorithms, the integration of multi-sensor data, and enhancing the generalization capabilities of deep learning models to ensure broader application in active safety systems. This paper provides insights into the current state of fatigue detection and outlines the key challenges and future directions for the technology's development.

Keywords: Recognition, Fatigue Detection, Deep Learning, Driving Safety

1 Introduction

Fatigue driving is defined as a decline in driving performance caused by prolonged physiological and psychological stress. As a significant threat to road traffic safety, the danger of fatigue driving is comparable to high-risk behaviors such as drunk driving and speeding, consistently ranking among the top three causes of traffic accidents. Although global traffic safety regulations have advanced significantly, fatigue driving persists as a challenge due to its hidden and gradual nature, making monitoring and early warning systems particularly difficult. Fatigue driving monitoring methods can be divided into subjective and objective monitoring. Traditional subjective monitoring methods, such as questionnaires and verbal reports, are simple to implement and can capture subjective experiences. However, they are limited by individual perceptual biases and delayed reporting, making real-time warnings difficult. In long-distance driving, drivers may be unable to accurately reflect their own state due to distractions or accumulated fatigue. This gap has driven the rapid development of intelligent fatigue

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detection technologies, especially breakthroughs in non-invasive visual analysis methods, which provide a key path for safety system innovation. Current fatigue driving monitoring technologies primarily focus on three paradigms: physiological signal monitoring, vehicle behavior analysis, and facial recognition.

Physiological signal monitoring directly reflects the driver's neural and physiological state by collecting bioelectric signals such as EEG and ECG. Although this method has high specificity, it requires electrodes to be fixed to the driver's head or torso, making it invasive. Invasive procedures not only interfere with driving comfort but also significantly reduce data reliability due to signal noise and motion artifacts in dynamic scenarios. Moreover, the complex data collection equipment and high deployment costs limit its large-scale application in onboard environments.

Vehicle behavior analysis builds early warning models based on vehicle dynamics parameters such as steering angle, lane deviation frequency, and throttle or brake patterns. This method can directly reuse existing onboard sensor networks without additional hardware support. However, its main drawback is latency. When significant lane deviation or abnormal operation is detected by the system, the driver is often already in a severe state of fatigue, and the lack of an early warning window limits the effectiveness of intervention.

Facial recognition-based visual analysis technology demonstrates superior overall performance through non-contact sensing and multi-dimensional feature fusion. This method captures dynamic facial information from the driver using an onboard camera, extracting multimodal fatigue-related features such as eyelid closure, pupil changes, mouth movements, and facial muscle micro-expressions using computer vision algorithms. It avoids the invasive drawbacks of physiological signal monitoring, overcomes the latency of vehicle behavior analysis, and improves the robustness of behavior feature recognition. It can achieve accurate early warnings with millisecond-level response times, providing key technical support for human-machine collaboration in L3-level and higher autonomous driving systems.

This paper systematically discusses how fatigue detection based on facial recognition is realized from two perspectives: fatigue detection based on single-dimensional features (eyes, mouth, head) and fatigue detection based on multi-feature fusion. It also explores the application and challenges of this technology in multi-scenario generalization.

2 Facial Feature Detection System

Facial features are varied, and different features of the face show different expressions under fatigue. Existing studies on facial fatigue features can be divided into single-dimensional fatigue feature monitoring and multi-feature fusion fatigue monitoring. Single-dimensional fatigue features analyze individual facial characteristics, while multi-feature fusion fatigue monitoring integrates multiple single features into a unified fatigue detection system through detailed dimension fusion and complex classification algorithms.

2.1 Fatigue Monitoring Based on Single-Dimensional Features

Common single-dimensional facial fatigue features include eye features, mouth features, and head posture features. This method has fast monitoring speed, low hardware requirements, and minimal computational power.

2.1.1 Eye Feature Analysis.

Eye dynamic features are one of the core indicators for evaluating driver fatigue. Fatigue leads to the relaxation of eyelid muscles, distracted visual attention, and abnormal eye movement patterns. Computer vision technology converts these physiological changes into measurable monitoring parameters. The current mainstream eye fatigue feature recognition system is based on three dimensions: PERCLOS (Percentage of Eyelid Closure), Blink Frequency (BF), and gaze direction analysis, which reflects visual attention levels. These features, through time series modeling and threshold determination, can effectively capture the continuous state changes from mild drowsiness to severe fatigue, providing reliable data for real-time warnings.

The method based on PERCLOS for monitoring driver fatigue is one of the most mature and accurate methods. PERCLOS evaluates fatigue by calculating the proportion of time that the eyes are closed within a specific time period. Existing standards include P70, P80, and EM modes, with P80 being the most commonly used. P80 refers to the percentage of time when the eyes are closed at least 80%, and it has been shown to have a significant correlation with the driver's fatigue level.

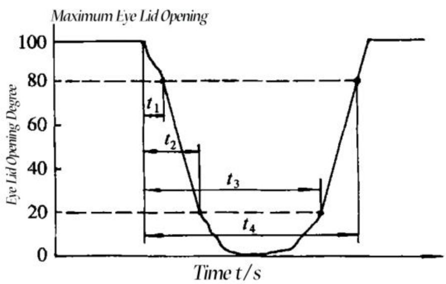

Fig. 1. Principle of Measuring PERCLOS [1]

As shown in Figure 1, the principle diagram illustrates the changes in eyelid opening and closing over time. By analyzing the curve characteristics, the duration of various eyelid closure levels can be precisely calculated. t_1 denotes the duration from full eye opening to 20% closure; t_2 represents the time interval from complete eye opening to 80% closure; t_3 and t_4 measure the intervals from full eye opening to 20% and 80% reopening, respectively. These time series data can be used to calculate the PERCLOS value f, which represents the percentage of time the eyes are closed in a specific period.

$$f = \frac{t_3 - t_2}{t_4 - t_1} \tag{1}$$

According to the P80 measurement standard, when the PERCLOS value exceeds 0.15, it indicates that the driver is in a state of fatigue driving. This threshold is based on extensive statistical analysis of experimental data and effectively identifies fatigue phenomena marked by prolonged eyelid closure.

Blink Frequency (BF) refers to the number of blinks per unit time. Normally, a well-rested person's eyes blink every 2-4 seconds, with each blink lasting 0.25 to 0.3 seconds. When the driver is fatigued, the blink frequency increases [2]. Therefore, the number and frequency of blinks can effectively reflect the driver's fatigue state.

Studies show that when a driver diverts their gaze from the normal road ahead for more than 2 seconds, the probability of a traffic accident doubles [3]. When the driver is in a fatigued state, the frequency of gazing away from the road increases. Therefore, gaze direction and duration can serve as effective feature parameters for detecting fatigue driving.

2.1.2 Mouth Feature Analysis.

Yawning is one of the primary manifestations of fatigue driving. Yawn frequency, mouth opening degree, and duration are important indicators for assessing fatigue. This process can be detected using Mouth Aspect Ratio (MAR), Percentage of Mouth Opening (POM), and shadow area between the lips. By setting appropriate thresholds, it becomes possible to distinguish between normal speech, smiling, and yawning behaviors, thereby improving the detection accuracy and reliability. MAR evaluates mouth openness by comparing the vertical and horizontal distances between the upper and lower lips. When this distance exceeds a set threshold, it indicates that the mouth is open. In yawn detection, attention is focused on the trend of MAR to identify the beginning and end of a yawn. Figure 2 shows the marking of mouth feature points [4].

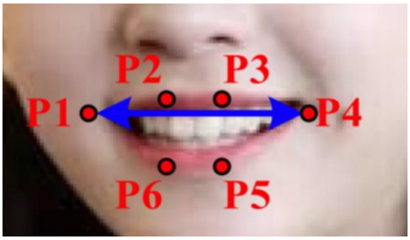

Fig. 2. Marking of Mouth Feature Points [4]

The MAR calculation formula is:

$$MAR = \frac{|P_2 - P_6| + |P_3 - P_5|}{2|P_1 - P_4|} \tag{2}$$

POM is the percentage of mouth opening time per unit time, similar to PERCLOS. The formula is shown as follows:

$$POM = \frac{\sum_i^N f_i}{N} \times 100\% \tag{3}$$

N is the total number of frames per unit of time, and f_i is the number of frames in which the mouth is opened, indicating the number of frames in which the mouth is opened per unit of time. A POM of more than 0.5 indicates that the driver has likely been in the mouth-open position for a considerable amount of time, which may also be interpreted as a sign of weariness [5]. Higher weariness is indicated by higher values for these two measurements.

A new approach is proposed to address the challenge where the mouth is covered by a hand during yawning [6]. The technique measures mouth opening using an adaptive threshold based on color segmentation, detecting the darkest region between the lips.This technique may detect variations in lip and skin color as well as lighting conditions. The detection method is shown in Figure 3.

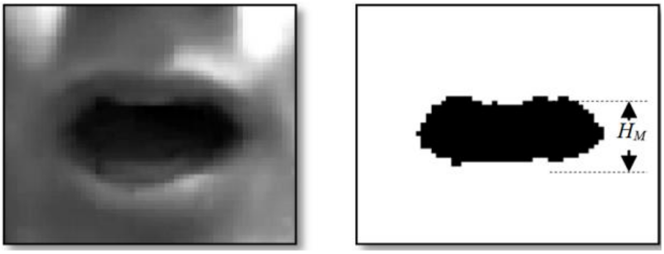

Fig. 3. Yawn Detection Based on Color Recognition [6]

2.1.3 Head Posture Feature Analysis.

When drivers are fatigued, they often have difficulty maintaining normal head posture, which is manifested as frequent nodding, tilting, or prolonged downward head movement. Therefore, head posture is an effective indicator for evaluating driver fatigue. The Euler angle is used to describe the driver's head posture, and the frequency of nodding and the duration of abnormal postures are used to characterize fatigue features. When fatigued, the driver may experience temporary lapses in attention, resulting in uncontrollable head muscle movement. After nodding, the posture is quickly adjusted, forming a repetitive pattern. Thus, head nodding can be closely monitored through the pitch angle in Euler angles.

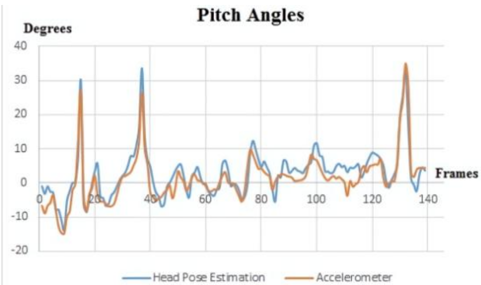

Fig. 4. Experimental Results of Pitch Angles Using Head Recognition and an Accelerometer Module at Night [7]

As shown in Figure 4, the pitch value increases significantly during nodding, and fluctuates during non-nodding moments, which may be due to the driver's inability to remain completely still and the vibrations caused by vehicle movement. Wongphanngam set a pitch angle threshold (30) that triggers an alarm when the driver's head nods beyond this limit. Sensitivity reached 93.75% on a dataset of 160 images. Real-world tests achieved 94.28% (daytime) and 95.13% (nighttime) sensitivity, validating robustness under varying illumination [7].

2.2 Fatigue Detection Based on Multi-Feature Fusion

Traditional single-dimensional fatigue recognition methods face limitations such as high false alarm rates and susceptibility to occlusion. Multi-feature fusion fatigue detection combines multiple single feature detection methods to not only enhance fatigue detection accuracy but also provide a deeper understanding of the interaction between the driver's physiology, behavior, and environment. This significantly improves the scientific and intelligent level of driving safety monitoring.

Li proposes a fatigue driving detection algorithm using an improved YOLOv3-tiny CNN for real-time face detection. The Dlib toolkit extracts facial features, identifying 68 key points to calculate Eye and Mouth Feature Vectors (EFV and MFV) [8]. SVM classifiers, personalized for each driver, are trained on these features and stored in a driver identity library. This enables identity verification and adaptive thresholds to reduce errors. Fatigue is measured using PERCLOS, blink frequency, and yawn frequency. The system achieves 95.10% accuracy, 20+ fps real-time performance, and is robust to lighting and occlusion, with personalized thresholds for better reliability.

Deng uses a modified Kernelized Correlation Filter (KCF) algorithm combined with Convolutional Neural Networks (CNN) to improve face tracking accuracy [9]. The system tracks 68 facial key points around the eyes and mouth, assessing fatigue through indicators such as blinking frequency, eye closure duration, and yawning frequency. The integration of Multi-task Convolutional Neural Networks (MTCNN) corrects initial tracking errors. This approach achieves about 92% accuracy and real-time performance, making it a practical solution for detecting driver fatigue using commercial cameras in various environments.

3 Industry Applications and Current Limitations

3.1 Industry Applications

In 2006, Toyota implemented a driver monitoring technology termed Driver Monitor in Lexus GS 450H. This technology uses highly sensitive infrared imaging to capture and analyze micro-expressions such as blink frequency and head movements in real-time to monitor the driver's state. The system recognizes the driver's behavior patterns and determines if fatigue signs appear, triggering sound and light alerts, as shown in Figure 5 [10].

Fig. 5. Toyota Driver Fatigue Monitoring System - Driver Monitor [10]

Driver Monitoring Systems (DMS) are advanced electronic systems integrated into vehicles to monitor the driver's behavior and state in real-time, with the goal of improving driving safety. These systems, based on machine vision, artificial intelligence, and sensor technology, capture and analyze facial features, eye movements, and head postures to assess whether the driver is fatigued or distracted, issuing warnings when necessary. DMS can be divided into indirect and direct systems, each with its own operating principles [11]:

Indirect DMS systems estimate the driver's fatigue level by analyzing their behavior in specific driving modes and a series of situational variables, such as circadian rhythms, driving duration, and monotonous driving conditions. The system analyzes parameters such as steering wheel speed, vehicle speed, vehicle-lane line position, and driving duration to evaluate the driver's current fatigue level. This method was a mainstream solution for early fatigue monitoring systems.

Direct DMS systems use infrared cameras installed near the vehicle's A-pillars or dashboard to monitor detailed head, eye, and facial movements of the driver in real-time. The data collected is processed using pattern recognition to determine whether the driver is fatigued. In fatigue monitoring, factors such as eyelid closure degree, blink frequency, and the proportion of time eyes are closed (PERCLOS) are considered, and machine learning algorithms are used to assess the fatigue level. The system focuses on parameters such as the driver's gaze direction, head pose angles, and hand movements as well. For instance, Kim [12] presents a real-time Driver Monitoring System (DMS) designed to detect driver inattention and drowsiness using facial landmark-based analysis. The system employs an infrared camera to capture video data, which is then processed to estimate the driver's head pose and detect eye closures. The DMS consists of two modules: one for head pose analysis to monitor attention levels, and the other for eye-closure recognition to detect drowsiness. By tracking head movements and the frequency of eye closures, the system can identify inattentive or drowsy driving behavior in real time. The method was tested using a custom dataset, showing high accuracy in detecting both inattention and drowsiness. This approach offers an efficient and practical solution for enhancing driver safety, especially under varying environmental conditions, and paves the way for future integration into commercial vehicles.

These two types of DMS systems, through different technical methods, monitor and assess the driver's state and are now integrated to form an efficient and mature monitoring system, providing important support for improving driving safety.

3.2 Current Limitations

Despite the technological progress made in facial recognition-based fatigue driving monitoring methods, there are still several key limitations that need to be addressed, which hinder the effective application of these technologies in real driving environments.

The image acquisition and analysis process under the limited onboard CPU computing power involves continuous high-resolution video stream data capture. Real-time execution of multi-level feature extraction and pattern recognition tasks results in a surge in computational load. This computational bottleneck not only affects system response speed but may also cause feature loss, ultimately leading to reduced timeliness and accuracy of the detection system.

Optical interference during dynamic driving scenarios poses a major technical obstacle. As the vehicle moves, natural lighting conditions exhibit unstable characteristics, including sudden changes in light intensity, mixed light sources, and alternating shadow areas. These factors severely disrupt the light consistency of facial images. Particularly, the mirror reflection effect caused by eyeglasses worn by the driver leads to artifacts that interfere with eye detection algorithms and cause feature drift. The unpredictability of optical noise poses challenges to biometric feature extraction process, directly affecting the signal-to-noise ratio of fatigue state detection.

Head vibrations caused by vehicle movement lead to motion blur in image sequences, reducing the spatio-temporal resolution of key facial action features. Additionally, facial accessories, geometric occlusion, hair distribution differences, and makeup coverage further increase the difficulty of detecting fatigue driving. These interference factors often lead to alternating false alarms and missed detections, severely limiting the generalization ability and practical deployment value of the detection system.

4 Conclusion

This paper introduces facial recognition-based fatigue driving monitoring technology, which utilizes non-contact visual analysis and integrates features such as eyelid closure, mouth movements, and head posture to efficiently identify the driver's fatigue state. This provides important technical support for ensuring driver safety. Compared with traditional physiological signal monitoring and vehicle behavior analysis methods, this approach's non-invasiveness, real-time performance, and multi-modal feature fusion significantly enhance the accuracy and applicability of early warnings. However, challenges persist in computational efficiency under resource-constrained onboard systems, optical interference in dynamic lighting conditions, and individual behavioral heterogeneity.

Future research should further explore the combination of lightweight algorithm architectures and edge computing technologies to optimize real-time processing performance. It is also necessary to strengthen multi-sensor data fusion strategies and integrate techniques such as infrared imaging to overcome the perceptual limitations of single visual modalities in extreme scenarios. Additionally, the generalization ability of deep learning models and adaptive feature extraction mechanisms still need to be developed to address individual driver behavior differences, such as habitual nodding and speaking movements. The collaboration between industry and academia should promote the establishment of standardized testing systems, covering multi-lighting conditions and driving scenarios, to accelerate algorithm iteration and engineering deployment. Through interdisciplinary innovation and hardware/software optimization, facial recognition-based fatigue detection technology holds significant potential to evolve into a cornerstone of next-generation active safety systems, ensuring proactive intervention in fatigue-related risks, providing a solid safeguard for driver safety.

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