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Driver Drowsiness and Fatigue Detection: An Investigation of Techniques and Challenges

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Abstract:

Fatigue driving stands as a critical contributing factor to road traffic accidents. To enhance safety, fatigue driving detection technology has evolved into a prominent research focus. This paper first introduces the concept of fatigue driving, then classifies detection methods into four categories based on different input sources. It provides a comprehensive review of studies on methods rooted in physiological features, facial features, vehicle behavior features, and multi-feature fusion—exploring their underlying principles and effectiveness, while revealing the technical bottlenecks of each method in practical applications. The paper aims to offer a theoretical reference for the optimization and innovation of this technology, furnish solid theoretical and data support for method refinement and technological innovation in subsequent research, and help readers in this field gain insights into future development directions. Ultimately, by summarizing the strengths and limitations of current detection approaches, this review highlights emerging trends such as deep learning-based multimodal fusion and real-time embedded detection, pointing toward more accurate, robust, and user-friendly fatigue monitoring systems in the future.

Keywords: Vehicles; driver fatigue; driver drowsiness detection; intelligent transportation.

1. Introduction

In recent years, motor vehicle ownership in China has been rising steadily, while the incidence of road traffic accidents remains high. According to data from the National Bureau of Statistics of China, 273,098 road traffic accidents occurred in China in 2021, with direct property losses reaching 1.45 billion yuan. Behind these grim statistics, the main factors contributing to road traffic accidents include lack of awareness of safe driving on roads, drunk driving, and drowsy driving. Among these factors, drowsy driving accounts for 14%–20% of the causes of road traffic accidents [1]. Prolonged high-speed driving can cause drivers to experience fatigue. If this fatigue is not alleviated, drivers will remain in a state of drowsy driving, with diminished self-control and stiffness in their limbs. In the event of an emergency, improper handling or failure to respond promptly will inevitably lead to accidents, injuries, and fatalities [2]. Therefore, people need to implement accurate drowsy driving detection to promptly issue warnings to drivers. From research in recent years, researchers have adopted targeted measures and used combinations of multiple methods to address the issue of driver fatigue [3].

The Karolinska Sleepiness Scale (KSS) is one of the earliest techniques used to assess sleepiness levels. However, it is not suitable for real-time drowsiness detection and prevention; instead, it is used as a benchmark for testing the accuracy of other drowsiness detection systems [4]. Later, with the development of science and technology, existing driver drowsy driving detection methods can be divided into four categories based on information sources obtained from different sensors: In terms of methods based on drivers‘ Physiological Features: These detection methods mainly collect data through sensors attached to the driver‘s body and can directly reflect the driver‘s physical condition. The main physiological features include: electroencephalography (EEG), electro-oculogram (EOG), electrocardiogram (ECG), electromyogram (EMG),etc.[5, 6]. Second, regarding methods based on Drivers‘ Facial Features: Currently, this technology mainly realizes real-time monitoring of the driver‘s eye blink frequency, mouth movements, head movements, and other features through computer vision and sensor fusion, so as to determine whether the driver is in a drowsy state [7-9]. Third, as for methods based on Vehicle Behavior Features: Fatigue can lead to a decline in drivers‘ operational capabilities, such as slower reaction speed, lack of concentration, and increased judgment errors. These changes are directly reflected in the vehicle‘s driving state. By detecting features such as the driver‘s steering wheel operations, vehicle speed, lane deviation, and driving trajectory, it is possible to determine in real time whether the driver is in a drowsy state [10, 11]. Finally, in the case of based on Multi-Feature Information Fusion: Single features often have information one-sidedness, while multi-feature fusion can compensate for defects through complementary information to achieve more comprehensive and reliable detection objectives [12, 13].

The aim of this paper is to systematically review and synthesize the existing research on the four mainstream drowsy driving detection methods. The rest of the paper is organized as follows. Section 2 is dedicated to describing and analyzing the four methods aforementioned. Section 3 then delves into the prospective challenges and future prospects. Finally, Section 4 offers a comprehensive summary of the entire paper and presents the concluding remarks.

2. Methods

According to the differences in input features, the methods to determine whether drivers are in a state of drowsy driving can be divided into multiple types.

2.1 Physiological Based Methods

Gromer et al. argue that extracting heart rate variability (HRV) data based on electrocardiogram (ECG) signals is an effective method for detecting driver drowsiness. In their study, they developed a low-cost and portable ECG sensor system. The hardware core of this system is a printed circuit board (PCB) that can be used as an Arduino shield, which includes dual inverted ECG channels and low-pass filtering. This PCB is capable of amplifying weak ECG signals and filtering out noise. Additionally, they developed an ECG signal simulator for software testing, as well as a real-time visualization function. Their experimental results show that this sensor can effectively extract the main ECG parameters, and when combined with facial recognition-based drowsiness detection, it can improve the drowsiness recognition rate under unfavorable conditions such as poor lighting or facial occlusion [5]. Puspasari et al. designed a driving drowsiness detection scheme integrating EEG signals and multiple influencing factors. They recruited 30 Indonesian college students, dividing them into two groups: the alert group (≥7 hours of sleep the night before the experiment) and the sleep-deprived (SD) group (<5 hours of sleep the night before). Participants drove a driving simulator for 1 hour, while EEG equipment collected alpha (α), beta (β), theta (θ) wave signals and calculated 4 brain wave ratios. Subjective sleepiness was recorded via the Karolinska Sleepiness Scale (KSS) every 15 minutes. Data processing showed: the SD group had higher α, β, θ wave power than the alert group; at the end of driving, the alert group saw increased θ wave, brain wave ratios and decreased β wave [6].

Physiology-based methods can directly reflect the driver‘s physiological state and have a scientific detection principle. However, they require the driver to wear contact sensors while driving, which may affect driving comfort, and the technology is relatively high in cost.

2.2 Facial-Feature Based Methods

To address the impracticability of intrusive driver fatigue detection methods such as EEG and ECG, Chen et al. developed a non-intrusive fatigue detection system based

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on drivers' eye features. They extracted eye features using the cascade classifiers of OpenCV and the 68-dimensional facial landmark detection model of Dlib. Through experimental comparison, they found that combining two algorithms improved the fatigue detection performance [7]. To address two key pain points in visual fatigue detection—face detection being susceptible to changes in illumination and facial expressions, and difficulty in distinguishing behaviors such as yawning and singing in a single frame leading to false detection—Fei et al. proposed a fatigue detection method based on sequential mouth features and Long Short-Term Memory (LSTM) network. Their method consists of two parts: one is to perform face detection using Histogram of Oriented Gradient (HOG) features combined with a Support Vector Machine (SVM) classifier, and then extract the mouth region from the detected face through cascaded regression trees; the other is to extract spatial features of the mouth region using Residual Network (Resnet), and finally determine fatigue based on yawning frequency [8].

In most cases, this method can identify facial features associated with fatigue. However, it is susceptible to the impacts of uneven illumination and facial occlusion, and requires algorithm optimization in complex environments.

2.3 Vehicle Behavior Based Methods

Due to the fact that existing methods based on Steering Wheel Angle (SWA) fail to consider road randomness and driver differences, and have poor feature extraction performance, Li et al. proposed a corresponding solution. They used approximate entropy to crop SWA sequences and designed a 4-layer Information Gain-Long Short-Term Memory (IG-LSTM) model. First, the filtered SWA data was input into the model; then, the fully connected layer extracted 15 SWA statistical indicators; next, the recurrent layer used a simplified LSTM to memorize driving habits; after that, information gain was applied to screen useful features; finally, the model output three states: awake, fatigued, and extremely fatigued [10]. Yan et al. designed a driver status monitoring system. This system captures images from the dashcam, obtains lane line coordinates via a lane detection algorithm to detect lane deviation, and then uses the Eye Aspect Ratio (EAR) value to judge eye opening and closing for fatigue detection. Finally, it combines the two results to conduct gradient judgment [11].

Vehicle behavior-based methods do not require contact with the driver and rely on existing sensor data of the vehicle. However, they are highly susceptible to interference from road conditions and have a strong lag—changes in the driver's operations occur later than the onset of fatigue.

2.4 Multi-feature Based Methods

To address the issues of existing single-feature fatigue detection methods being susceptible to interference and having low accuracy, Yu et al. proposed a multimodal Long Short-Term Memory (LSTM) network-based fatigue detection model that integrates Photoplethysmography (PPG)-derived Heart Rate Variability (HRV), facial features, and head postures. This model improves the detection accuracy and reliability in real-road scenarios, providing a timely and accurate early warning solution for fatigued driving [12]. Zhao et al. extracted drivers' facial features using Convolutional Neural Network (CNN), and combined these facial features with the R-R interval features of electrocardiogram (ECG) and vehicle state features to form multivariate time series. Then, they utilized the self-attention and masking mechanisms of Gated Transformer Network (GTN) to capture channel-wise and step-wise (temporal) correlations, and finally verified the feasibility of multimodal fusion in fatigue detection for autonomous vehicles (AVs) [13].

Methods based on multi-feature information fusion achieve multi-dimensional information complementarity, and exhibit strong detection comprehensiveness and robustness. However, they have high system complexity, require processing of multi-source heterogeneous data, and have high requirements for computational resources.

3. Discussion

3.1 Challenges

In recent years, driven by the growing demand for traffic safety and the advancement of intelligent transportation systems, significant progress has been made in driver fatigue detection technology—with innovations ranging from single-modal physiological or visual sensing to multimodal fusion approaches as explored in relevant research. However, the widespread real-world application of this technology still faces prominent technical challenges, among which adaptability to complex driving environments remains a primary bottleneck. Specifically, scenarios involving unpredictable illumination changes—such as sudden shifts from bright daylight to dim tunnels, low-visibility nighttime driving, or harsh backlight conditions that wash out critical visual details—and accidental camera occlusion by in-vehicle objects often disrupt detection workflows. These issues are particularly impactful for vision-based modules, a core component of many fatigue monitoring systems, as they directly impair the extraction of fatigue-related cues [12]. Although infrared technology is frequently proposed to mitigate interference from accessories like sunglasses, it is not a panacea: under intense backlight, the inherent contrast between facial features and the background is still significantly reduced, degrading the quality of image data and thus the reliability of subsequent fatigue assessments.

On the hardware front, the most direct drawback lies in the high demand for computing power and storage capacity. This is especially true for advanced fatigue detection models that process multimodal time-series data in real time—including high-resolution facial landmarks, continuous ECG signals, and dynamic vehicle state parameters. While integrating additional arithmetic units or expanding memory can alleviate bottlenecks like latency and data throughput, it inevitably increases overall system complexity, raises manufacturing costs, and may impose practical constraints on deployment in low-cost vehicle models. Software algorithms, meanwhile, require continuous iteration to keep pace with evolving driving scenarios. For example, as drivers encounter diverse environments or new sources of interference, algorithms must be retrained or fine-tuned to maintain accuracy—particularly for distinguishing subtle fatigue levels, which are critical for triggering timely and appropriate early warnings. Without such updates, even state-of-the-art models may struggle to generalize beyond controlled test conditions.

Beyond technical performance, privacy protection represents another pressing concern. Most fatigue detection systems collect and process sensitive driver data, including real-time facial images, physiological signals, and driving behavior patterns. If not secured through robust encryption, anonymization, or access control mechanisms, this data risks misuse—undermining driver trust and acceptance of the technology. Addressing this challenge is therefore not only a technical necessity but also a key enabler for the widespread adoption of fatigue detection systems in practical automotive applications [14].

3.2 Future Prospects

To address the aforementioned challenges and unlock the full potential of driver fatigue detection systems in real-world automotive scenarios, future advancements will focus on three interconnected core directions—each tailored to resolve specific pain points while enhancing overall practicality.

First, adaptive multi-sensor fusion will be pivotal in boosting environmental robustness. Beyond simply combining visible-light cameras with millimeter-wave radar and thermal imaging, future systems will integrate real-time data calibration and dynamic weight assignment: for instance, millimeter-wave radar will take precedence when camera lenses are occluded by in-vehicle objects, while thermal imaging will maintain stable facial feature capture in extreme low-light conditions. Complemented by advanced adaptive illumination algorithms—including auto-exposure adjustment and backlight suppression—this fusion will ensure consistent extraction of fatigue cues (e.g., eye closure duration, head pose changes) even in highly variable environments, directly addressing the long-standing adaptability bottleneck.

Second, efficient hardware-software co-design will alleviate resource constraints and cost barriers. On the hardware front, next-generation low-power edge chips need to achieve a certain level of power reduction compared to current in-vehicle processors, enabling their application in low-cost entry-level vehicle models. For software, lightweight deep learning techniques can halve the model size while maintaining over 95% detection accuracy, reducing memory usage and latency to meet real-time requirements. Additionally, federated learning frameworks can support collaborative model training across vehicle fleets: each vehicle performs local training on its driver data (without uploading sensitive information to a central server), allowing the system to adapt to the behaviors and scenarios of different drivers without compromising privacy [15].

Third, privacy-by-design principles and regulatory alignment will be critical to building driver trust. Future systems will embed privacy at every architectural stage: differential privacy will add controlled noise to facial data to prevent identity recognition, while end-to-end encryption will secure data transmission between sensors and on-board controllers. Moreover, systems will comply with global automotive data regulations by implementing transparent data policies—such as clear user consent mechanisms and automatic data deletion after 72 hours—to mitigate concerns about misuse.

In summary, the synergy of these three directions will not only resolve technical hurdles but also foster user acceptance, driving the seamless integration of fatigue detection technology into intelligent transportation systems and ultimately contributing to a 20–25% reduction in fatigue-related traffic accidents.

4. Conclusion

This paper conducts a comprehensive review of fatigue driving detection technologies, classifying existing methods into four categories, including those based on physiological features and facial features. Through discussion and analysis, it is clarified that the detection method based on multi - feature fusion represents a crucial direction for future research. Future studies should further overcome the bottleneck in adapting to complex environments, explore low - cost and high - performance hardware solu-

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tions, enhance the innovation of multi - modal data fusion algorithms, and establish privacy protection mechanisms. This will facilitate the development of fatigue driving detection technology towards greater accuracy, reliability, and accessibility, thereby providing more robust guarantees for road traffic safety.

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