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REVIEW ARTICLE

Advancements and Perspectives in Fatigue Driving Detection: A Comprehensive Review

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Abstract

Driver fatigue is a significant contributor to road accidents worldwide. Timely detection and alert systems for driver fatigue can substantially enhance driving safety and reduce traffic-related casualties. This article presents a comprehensive review of the recent advancements in driver fatigue detection technologies. It categorizes and evaluates detection methods based on physiological signals, behavioral characteristics, vehicle dynamics, and information fusion techniques. Additionally, it scrutinizes the prevalent datasets and methodologies employed in fatigue detection, offering valuable insights for future research directions. Our analysis emphasizes the importance of integrating multimodal data to improve detection accuracy and reliability, underlining the potential of information fusion approaches in developing robust fatigue detection systems. This synthesis aims to serve as a foundational reference for researchers venturing into the domain of driver fatigue detection, paving the way for innovative solutions to combat fatigue-induced road accidents.

Keywords: Fatigue driving, Detection method, Information fusion, Dataset.

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1 Introduction

With the increase in the number of cars, there are more and more traffic accidents. Countless people's lives are threatened by all kinds of traffic accidents every year. The "Global Road Safety Report" pointed out that the number of deaths caused by road traffic accidents has increased to 1.35 million people per year, that is to say, nearly 3,700 people die in traffic accidents worldwide every day [1]. In the United States and Europe, drowsiness is responsible for 21 percent of all fatal crashes [2].

Fatigue is a symptom of weakness caused by a high concentration of body or mind for a long time [3]. Most drivers still lack awareness of the danger of fatigued driving behavior. When the driver is fatigued, there will be characteristics such as slower reaction speed, hearing loss, inattention, and weakened sensory functions, causing the driver to be unable to make timely judgments on the actual road conditions and resulting in traffic accidents [4]. If the driver is alerted immediately when the driver is fatigued, the possibility of traffic accidents can be greatly reduced. Studies have shown that when the driver receives a warning just a second before the danger appears, it may prevent some of car accidents from happening eventually [5]. Fatigued driving leads to a high accident rate and serious consequences. Therefore, it is very important to accurately identify the fatigue state of the drivers and to make timely warnings.

This article aims to summarize the development and research trends of fatigue detection methods and provide guidance for future research. Section 2 outlines these detection methods. Section 3 discusses the datasets obtained in the detection method. The fourth section makes a comparative study of various methods, and the fifth section is a summary of this research.

2 Fatigued Driving Detection Methods

Fatigued driving has the characteristics of strong concealment and difficulty in quantification, which makes it difficult to detect and judge the fatigue degree of the driver. Many experts and scholars at home and abroad are actively studying fatigued driving, and have made a mass of research results. Meanwhile, various detection methods have been explored, and considerable progress has been made. This section sorts out the fatigue driving detection methods, and divides the research articles into four categories according to the characteristics of the detection target, as shown in Fig. 1.

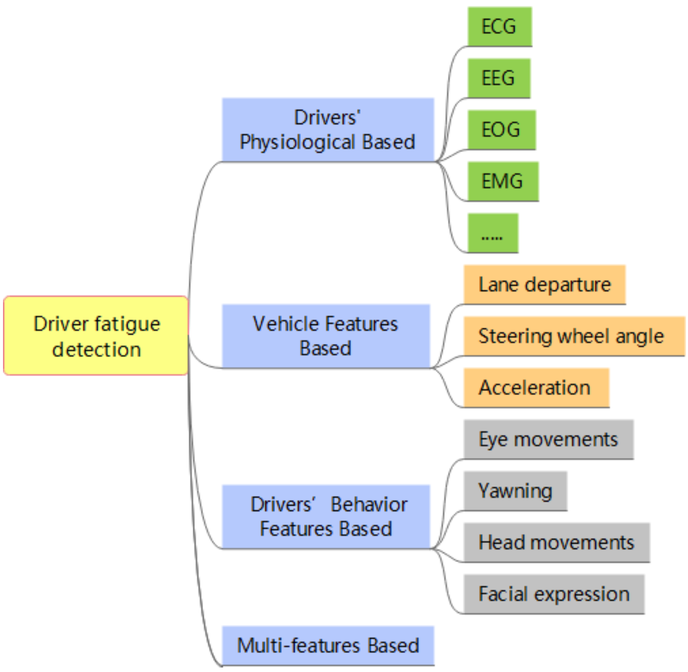

Figure 1. Summary of fatigue detection methods from the literature.

2.1 Summary of fatigue detection methods from the literature

Physiological feature-based drowsiness detection techniques have been widely used by researchers [6]. The physiological signals commonly used in detection methods include electroencephalogram (EEG), electrocardiogram (ECG), electromyography (EMG) and so on. Professional measuring instruments can detect the physiological signals related to the driver's fatigue state to determine whether the driver is fatigued. The block diagram of the driver's sleepiness detection system based on typical physiological signals [7] is shown in Fig. 2.

1) ECG Based Detection

HRV(Heart Rate Variability) index in ECG are crucial physiological indicators to judge a fatigued state [8]. Francesca Trenta et al. [9] detected and extracted facial landmarks to reconstruct PPG signals, using computer vision techniques. Through PPG detection and analysis of HRV signals, the HRV frequency domain of the driver's heart rate time series is calculated to obtain the information of the car driver's drowsiness. This method is based on a mixed Long ShortTerm Memory (LSTM) – Convolutional Neural Network (CNN) system [55–57]. Jinwoo Kim et al [10]. proposed a new spectrum measurement method suitable for HRV respiratory power spectrum. They also proposed the weighted mean (WM) and weighted standard deviation (WSD) of the power in the high-frequency band. Respiration characteristics are investigated which are derived from HRV signals. This respiration measurement is used in combination with HRV measurement to further improve the prediction accuracy. These results indicate that this method has a good indicator of drowsiness detection.

2) EEG Based Detection

The EEG signal can be decomposed into 4 rhythms (α wave, β wave, θ wave, δ wave). When the human body is fatigued, the energy of the δ wave and θ wave rhythm will increase, while the energy of the α wave and β wave rhythm will decrease, which can be used to determine the fatigue state [11]. Based on the relationship between frequency band signal change and driver fatigue degree, the detection algorithm can accurately judge driver fatigue degree by using real-time EEG signals.

Belakhdar et al. [12] proposed a single-channel automatic driver drowsiness detection method based on artificial neural networks (ANN). Nine features are calculated from an EEG channel using the Fast Fourier Transform (FFT). After introducing these features in an ANN classifier, the classification accuracy of drowsiness and alertness detection is 86.1% and 84.3%, respectively. S. S. Poorna et al. [13] propose an interesting approach principal component analysis (PCA) of EEG data to extract dominant ocular pulses, and obtain two sets of data: one set of eigenvectors representing eye blinks only and the other set of

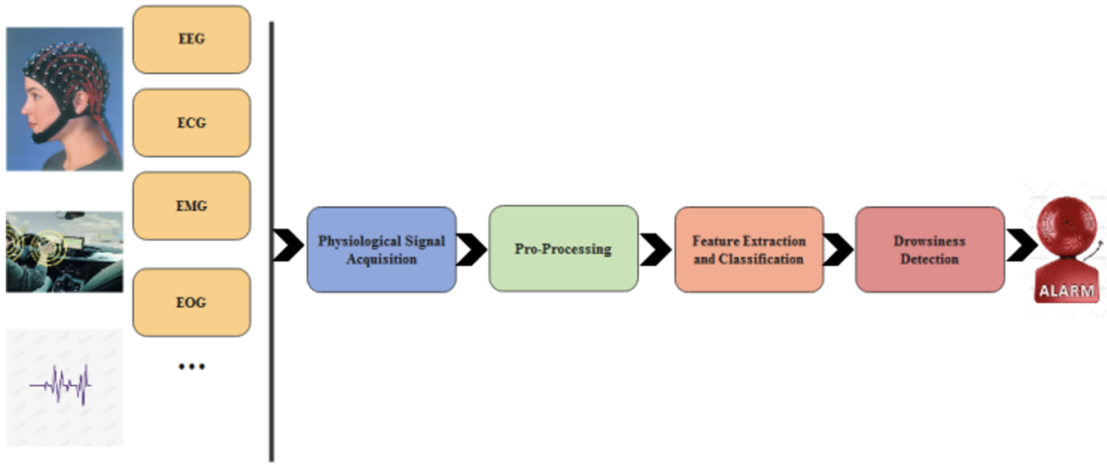

Figure 2. The block diagram of the driver's drowsiness detection system based on typical physiological signals.

eigenvectors excluding blinking. The accuracy of KNN classifier and ANN classifier is 80% and 85% respectively for the feature classification to identify the alert or awake, sleepy and sleeping state of the driver.

3) EOG Based Detection

The EOG signal is a biofeedback of the electric field potential generated between the cornea and the retina and usually varies between 0.05 and 3.5 mv. Any kind of eye activity, such as blinking and eye movements, can change the potential difference, resulting in a change in the EOG signal [8]. The potential difference between the cornea and the retina is measured by the electrode in the upper and lower eyelid, and the movement state of the eyeball is measured according to the differential signal at both ends of the electrode, so as to judge the driver in fatigue state. Zheren Ma et al. [14] proposed a wearable sleepiness detection system. EOG signals are collected by EOG electrodes in the system. Then the signals which are filtered and amplified are transmitted to smartphones wirelessly through Bluetooth. Then the ARIMA model is used for prediction. Experiments showed that the device can effectively capture the driver's EOG signal, and can effectively alarm the driver 0.5 seconds ahead of time. Wei-Long Zheng et al. [2] used forehead electroocumograms (EOGS) obtained by wearable dry electrodes to get the changes of the electrostatic potential of eyes at a certain moment, so as to determine fatigue.

4) EMG Based Detection

Due to the influence of the driver's clothes, most of the driver fatigue detection takes the surface EMG signal as the research object. The characteristic parameters used to evaluate the fatigue state include the average frequency of EMG, the amplitude of EMG, and so on. When the frequency of EMG drops sharply, it indicates that the driver is in a state of fatigue. Mohammad Mahmoodi et al. [15] detected drowsiness by classifying surface electromyography (EMG) signals. First, the surface EMG signals of the upper arm and shoulder muscles are measured. The signals divided into periods of 30 seconds. Then five features which are range, variance, relative spectral power, kurtosis, and shape factor are extracted. Finally, six classifiers are used for classification. The results showed that the K-nearest neighbor classifier is the best predictor, with an accuracy of 90%.

2.2 Detection methods based on vehicle features

By monitoring various data during vehicle driving and the changing process of data, such as driving speed, steering angle, and lane deviation, multivariate correlation analysis is conducted between the changing driving data and the driving data of vehicles under normal conditions [6]. The rationality of driving is judged according to the deviation of the two data, and the abnormal driving behavior and fatigue degree are revealed from this perspective. Fig. 3. describes the general system frame structure using a fatigue detection system based on vehicle behavior characteristics [7].

1) Lane Departure Detection

In order to avoid traffic accidents, the extent to which the vehicle deviates from the road guidance line can be analyzed to achieve the purpose of judging the fatigue degree of drivers. Alhadi Ali Albousefi et al. [16] proposed a nonlinear binary support vector machine (SVM) technique to predict unintentional lane departure. The system was divided into two

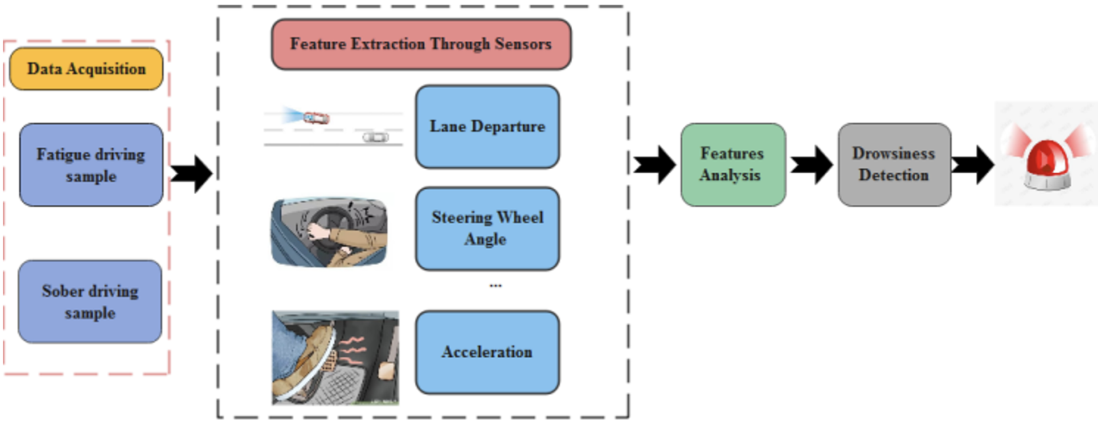

Figure 3. General system frame structure using a fatigue detection system based on vehicle behavior characteristics.

stages. In the first stage, nine sets of variables such as the lateral position, lateral acceleration, and speed of the vehicle were used as input variables for the training of SVM, and the combination of lateral position and lateral velocity was obtained the best effect on SVM1 and SVM2. In the second stage, the false-positive errors generated by the SVM in the first training process were used as part of the training data to train the same SVM, so as to minimize the number of false-positive errors. The experimental results proved that the two-stage training support vector machine method improved the accuracy of lane departure. Support vector machine (SVM) has a wide application prospect in lane departure prediction.

2) Steering Wheel Angle Detection

When the driver is in a state of fatigue, he may hit the steering wheel randomly and hold the steering wheel for a long time, etc. Therefore, the change of steering wheel rotation angle can reflect whether the driver is in a state of fatigue during driving.

Li et al. [17] collected steering wheel angle data (SWA) through a sensor installed on the steering lever, extracted useful information from the SWA data of the steering angle, and realized the function of online detection of driver fatigue state. The irregularity of the random time series of steering wheel angles can be quantified by the ApEn feature. Therefore, the system first extracted the approximate entropy (ApEn) from the real-time steering wheel angle time series with a fixed sliding window. Then, set an appropriate deviation and use adaptive piecewise linear fitting to linearize the ApEn feature sequence. Next, the warping distance between the linear feature sequences of the sample data is calculated. Finally, a classifier was designed based on the decision model, and the warp distance was used to judge the drowsiness of the driver. In order to verify the effectiveness of the system, the experimental data came from 14.68 hours of driving data under real road conditions. The results showed that the system can work online with an average accuracy rate of 78.01%, which has practical application value [53, 54].

3) Acceleration Detection

During the driving of the vehicle, it can be determined that the driver may be fatigued by monitoring the changes of acceleration parameters of the vehicle. Wang et al. [18] combined steering wheel angle information with different time window sizes, longitudinal acceleration, and lateral acceleration data information of the vehicle as input training data. The random forest algorithm was used to analyze the classification data of the driver's vehicle parameters in the fatigue state and the normal state to judge the driver's fatigue state. Comparing the above three indicators respectively, it can be concluded that the combination of 20s lateral and longitudinal acceleration parameters can detect fatigue more effectively. The results showed that the detection accuracy of fatigued driving behavior was 84.8%.

2.3 Detection methods based on drivers' behavior features

When the driver is in a fatigued state, he will have obvious characteristics such as drifting left and right eyes, gradually reducing the degree of eye-opening, increasing blinking frequency, yawning, and frequent nodding [19, 58–61]. The detection method based on the driver behavior characteristics is to collect the driver's image information, extract the features of the relevant parts, and analyze them, so as to judge whether the driver is fatigued. At present, the available features of this type of method mainly include eye features, mouth features, head posture features, and facial expression features, etc [20]. The block diagram of the driver's drowsiness detection system based on typical facial features is shown in Fig. 4 [7].

1) Eye Features Detection

The driver's eyes state is an important feature reflecting the fatigue state. Studies have pointed out that when the driver enters a fatigued state, his blinking frequency is reduced, and the time of closing his eyes is significantly increased compared with the normal state, the time of opening his eyes is also reduced, and the degree of eye-opening is also reduced to a certain extent [5]. If falling into a deep state of fatigue, his eyes may in a closed state for a long time [21]. The degree of fatigue is usually determined by percentile eyelid closure (PERCLOS), blink rate (BF), and maximum closure duration (MCD).

Zhuang et al. [22] designed a streamlined network, which is consists of a segmentation network and a decision network to detect drivers' drowsiness. The segmentation network has a light U-Net structure and classifies human eye images at the pixel level. Then accurately extract the pupil and iris features in the video image. The extracted feature map is used to guide the estimation of eye openness in the decision network. The method is tested by the National Tsinghua University NTHU-DDD Video dataset. The result is that the fatigue detection accuracy reached 96.72%. Feng You et al. [23] proposed a real-time sleepiness detection algorithm for driving based on individual differences. Firstly, a Deep Cascaded Convolutional Neural Network (DCCNN) is used to detect the face region in real-time video and obtain the coordinates of the marking points of human eyes. The eye length-width ratio (EAR) is then calculated to determine whether the eye is open or closed. The aspect ratio of eyes was input into a fatigue classifier based on SVM. Finally, the trained classifier can monitor the driver's status online in real-time. The system is divided into two modules: offline training classifier and online monitoring, which effectively improves the performance of the algorithm, and the accuracy rate of fatigue detection is 94.8%.

2) Mouth Features Detection

Normally, when a person is awake, his mouth is usually closed or speaking (i.e. open and close). But when people feel sleepy, they tend to yawn, which is an uncontrollable opening of the mouth to increase the oxygen supply to the body. At this time, people's mouth opens wider than usual. When the driver is tired, the mouth state is different from the driver's speaking or normal driving, so the mouth state can also reflect the driver's fatigue state to a certain extent. Therefore, the characteristics of the mouth can be used to detect the driver's drowsiness. In research, characteristics such as the shape of the mouth, the position of the corners of the mouth, and the degree of mouth opening are often selected to determine whether the driver is drowsy or yawning [21].

Belhassen et al. [24] proposed a method to detect the yawning state of drivers. This method is based on the analysis of the temporal and spatial description after the detection of the lip edge. Firstly, the Viola-Jones method is used to identify the face location and segment the region of interest. Then, a contour-based deformable model is used to extract the signals describing various states of the oral cavity to identify the state of the driver's yawning. Although the method can detect drowsiness by detecting yawns, it fails to locate the mouth properly, such as when a yawn is covered with a hand or when a male driver has a beard. Therefore, the authors suggest that a hybrid approach is more effective.

3) Head Movements Detection

A drowsy person may nod, causing a sudden change in head position. Therefore, it is feasible to detect the driver's head position to determine whether the driver is in fatigue state. Yang et al. [25] proposed a driver drowsiness detection system that uses RFID technology. The system judges nodding movements by measuring the phase difference between two radio frequency identification tags attached to the back of the hat the driver is wearing. Combining with an unsupervised LSTM model to learn nodding features can effectively detect the fatigue state of drivers. This is an effective and low-cost method.

4) Facial Expression Features Detection

Facial expressions include eyes, eyebrows, cheeks, and mouth. If a driver is tired, some of the muscles in his face become stiff, which can interfere with minor movements. Zhao et al. [26] proposed a method to classify driver's drowsiness expressions using dynamic facial fusion information and a deep belief network (DBN). First, extracted the landmarks and textures of the eye and mouth regions that complement each other from each image sequence. Then DBN is used to create a representation of the combined information to classify the driver's drowsy

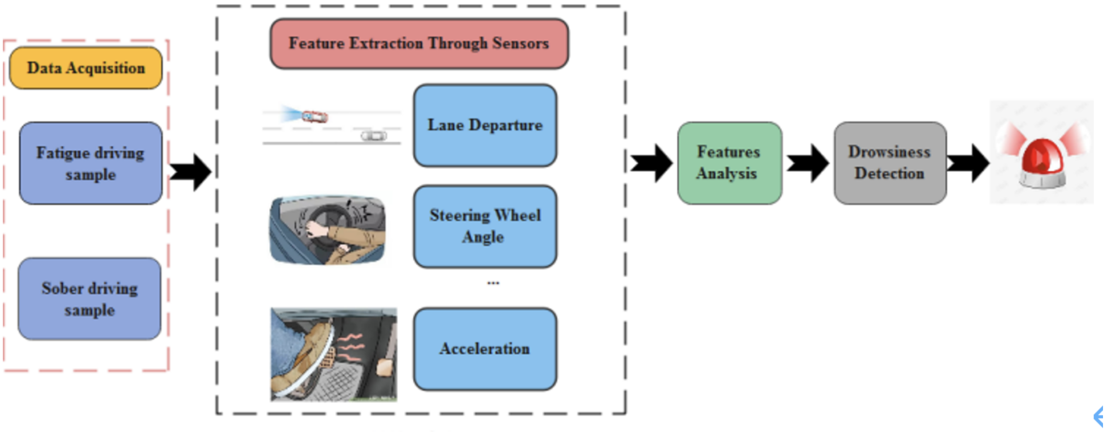

Figure 4. The block diagram of the driver's drowsiness detection system based on typical facial features.

facial expressions.The authors evaluated the effects of different facial partitions and different frame rates on the recognition accuracy, and the results showed that combining the eye and mouth regions achieved high recognition accuracy and showed the most efficient performance in 24 frames/SEC video. The method has an average accuracy of 96.7%.

2.4 Detection methods based on multi-features

The accuracy of a single fatigued driving detection technology is limited. In order to improve the accuracy of drowsiness detection, two or more of the above three methods are integrated, which is the driver fatigue detection method based on multi-information fusion. These methods actually use a variety of characteristic parameters or multiple detection methods to comprehensively determine the fatigue state. Its key research work is to build a reasonable and effective information fusion decision model according to the influence degree and reliability of various information. With the wide application of deep learning in various fields, the fatigue detection method of deep learning based on multi-feature information fusion has also developed rapidly.

In discussing the detection method of fusing the drivers' physiological characteristics , Huo et al .[27] used EEG and forehead EOG, combined with a regularized manifold information extreme learning machine (GELM) to detect driver fatigue. First, the wavelet method and the peak detection algorithm were used to extract 36 EOG features such as blinking, fixation, and saccade, and the power spectral density (PSD) and difference entropy (DE) of EEG were extracted. Then the discriminant graph regularization extreme learning machine (GELM) was introduced to assess the fatigue level of drivers respectively. After the EEG and forehead EOG regression models were trained, the fusion method was used to compare the effects: the feature vectors of the two signals were concentrated into a large feature vector, which was used as the input of the training model. The average of the two regression results would be calculated as the final estimated fatigue level. The experimental results show that the prediction of feature fusion based on GELM has achieved better results. Jasper Gielen and Jean-Marie Aerts [28] monitored the temperature and heart rate of the nose and wrist of 19 driving simulation participants and found that the classification accuracy of integrating these characteristic variables reached 89.5%. They concluded that physiological characteristics related to temperature regulation could be used to detect the drowsiness of drivers.

In the vehicle multi-feature information fusion detection methods, McDonald et al. [29] designed a model with steering Angle, pedal input, speed, and acceleration as inputs, combined with a dynamic Bayesian network that takes into account the time dependence between sleepiness and wakefulness. The dynamic Bayesian network algorithm was verified by taking 72 participants driving the national advanced driving simulator as an example. This algorithm reduced the false alarm rate of driver fatigue in highway and rural environments. Zhenlong Li et al. [30] firstly obtained vehicle performance indicators (speed, acceleration, brake pedal, accelerator pedal, steering angle, and lateral position), and then analyzed and evaluated these indicators to test their correlation with drowsiness in different road sections. Then constructed the classifiers based on k-nearest neighbor, support vector machine, and artificial neural network. The experimental results showed that the SVM classifier achieved the fastest classification time and the highest accuracy rate (80.84%).

In the multi-feature information fusion detection methods based on driver behavior, Guo and Markoni [31] proposed a method for real-time driver drowsiness detection using a combination of the convolutional neural network (CNN) and the long short-term memory (LSTM). Firstly, the MTCNN algorithm is run to obtain the position of the driver's face, eyes, and mouth, and crops the eyes and mouth area. The processed images are input into the left eye CNN network, the right eye CNN network, and the mouth CNN network to extract fatigue features. Finally, the LSTM trains time analyzer to determine that the driver is in a sleepy state. Based on the features of eyes and mouth, a multi-task neural network (ConNN) model for driver drowsiness detection is established [32]. DLIB algorithm is used to accurately identify the driver's eyes and mouth area. The ConNN model is used to train the system and determine drowsiness parameters which means using PERCOS and FOM parameters to determine the drowsiness degree. Finally, the state of the driver is evaluated as "very tired, not too tired and not tired" according to fatigue parameters. The accuracy of the model on YAWDDD and NTHUDD data is 98.81%.

In addition, different types of multi-feature fusion methods to detect fatigue have also achieved good results. Nurul Aisyah Binti Amirudin et al. [33] combined physiological and behavioral measures to detect drowsiness. The authors extracted the characteristics of δ, θ and α bands from EEG signals, and extracted the eye states from video sequences, with special attention to eye closure. The extracted EEG features are classified by using methods which are KNN, ANN, and SVM. The Viola-Jones algorithm was used to detect the eye state. Finally, the physiological characteristics of the θ band are used in combination with the P4 channel eye state to detect the driver state. Qaisar Abbas [34] proposed a hybrid drowsiness detection system that integrates visual and non-visual features. First, dual cameras are used to detect the driver's face, so that PERCLOS, EAR, and MAR values could be measured. At the same time, the heartbeat (BPM) is taken from the ECG sensor readings. Finally, the hybrid drowsiness system can detect the driver's state by combining the ratio of AER, MAR, and BPM. The experimental results show that the hybridization drowsiness detection accuracy rate reaches 94.50%.

3 Dataset Acquisition

Dataset is an indispensable and important element in model training and result prediction. In order to judge whether the driving driver is fatigue, it is necessary to obtain data from cameras, various sensors, other nearby vehicles and roadside infrastructure. High-quality data is the key to make the drowsiness detection system reliable. However, collecting drowsy driving data on real roads is too risky. Most researchers conduct experiments in driving simulators, which are similar in function to road experiments and are used for behavioral and physiological performance analysis [35].

In order to obtain physiological parameters data, the sensor devices with high sensitivity are needed. Connecting sensors directly to the driver may interfere with actual driving. Many authors choose small and wearable embedded devices to minimize interference to drivers' behavior when obtaining physiological data. Subha et al. [36] collected data using an EEG headset named NeuroSky Mindwave, which can measure raw brain waves and analyze EEG signal quality. Cheon and Kang [37] used a biosensor embedded in a wrist-type wearable device to obtain physiological data from the ECG signal, which was extracted from the photoplethysmography (PPG) sensor. Due to the differences in acquisition equipment and physiological signals, designers usually use simulated cockpit environment to build their own datasets. They collect physiological data d from 10-30 healthy subjects to measure the difference between alertness and drowsiness [38].

Vehicle characteristic data is collected by sensors mounted on the vehicle. These sensors monitor changes in lane departure, steering angle and acceleration on the car's pedals. The vehicle characteristic dataset is usually collected and established by the author himself. Due to the high sampling frequency and high noise of such data sets, it is a big problem to apply artificial neural network to classify such a large and complex input dataset [18].

The driver behavior dataset is collected by the camera. Facial images taken directly at the driver's camera have high resolution, and some of these systems use specially designed infrared (IR) cameras or stereo cameras to improve clarity [20]. The captured video image are susceptible to illumination and occlusion. Researchers collect their own datasets usually by setting some parameters, such as lighting, weather conditions, lighting conditions, etc. However, if the proposed method is evaluated using the author's private dataset, the applicability of the proposed method will be limited. Video captured in other available datasets (captured under various actual driving conditions and driving scenarios) and real-time capture may be difficult to achieve the high-precision results claimed by the author [3].

Collecting data alone requires the preparation of laboratory equipment and a certain number of volunteers. Volunteers may take 1-4 hours. Many researchers have encountered obstacles in the amount of data [6]. The public datasets can be used by any researcher. These datasets are helpful to the research and evaluation of algorithms. The public datasets used in this literature reviewed are shown in Table 1:

4 Discussion

The detection method based on the driver's physiological characteristics has the advantages of high reliability, high sensitivity, and strong anti-interference ability.However, professional and expensive detection devices are required to support the testing, which costs a lot. This method requires the driver to wear the corresponding instrument while driving, and it needs to be in direct contact with a specific part of the driver's body. It may give the driver an uncomfortable feeling in the actual driving, which may affect the driver's driving and easily interfere with the driver's line of sight. It not only can't assist the driver to drive safely, but also may lead to traffic accidents. Therefore, such methods have poor practicability and are difficult to promote and use in actual driving environments [7].

The fatigue detection method based on driving data is a method in which vehicle speed, steering wheel angle, and vehicle lateral distance are the main characteristics. This type of method is based on the driver's operation and control of the vehicle and judges the driver's fatigue state by combining the road conditions and vehicle driving state information [6]. It has the advantages of convenient detection and simple algorithm. However, the disadvantage is that it is greatly affected by road conditions, driving environment, vehicle models, individual differences of drivers, and driving habits, and its reliability is low [21]. In addition, the method requiring lane line detection to determine the status of vehicles is only suitable for standardized roads with lane lines, and the identification accuracy is very low on roads without lane lines. Therefore, the detection effect of this method only focusing on vehicle driving characteristics is not outstanding.

The fatigue detection method based on the driver's behavior characteristics usually evaluates the driver's fatigue degree according to the behavior characteristics of the driver's head and face (eyes, mouth, etc.) in a fatigued state. The advantage of the method is a non-intrusive detection and the selected features reflecting fatigue are more obvious and direct. It will not cause any interference to the driver and have strong operability Such methods not only have high accuracy, but also have the advantages of high real-time performance, low cost, and high accuracy. With the rapid development of computer vision technology, the fatigue detection algorithm based on driver behavior characteristics is becoming more and more mature and rapid. Therefore, this method has stronger applicability compared with the other two kinds of methods and is currently the most concerned and widely used method.

The fatigue detection method based on multi-features merges fatigue characteristics such as driver behavior, facial information, vehicle operating parameters, and physiological parameters are fused to analyze fatigue state. This type of method has a greater advantage in detection accuracy, but more sensors and other equipment will be used for the needs of information collection, the hardware cost will increase, and the failure rate will increase. In addition, due to the increase of information processing, the operation cost of the system increases, and the real-time performance has a certain disadvantage compared with other algorithms.

In addition, using different types of classifiers to train the data will also affect the efficiency and accuracy of the fatigued detection system. The surveyed papers used DL techniques to address their concerned issues. Among them, SVM, LSTM and CNN classifiers are favored by authors in drowsiness detection systems. SVM is an excellent binary classification model. It has been used in many articles [10, 15, 16, 20, 23, 27, 30, 35, 37, 43], and completed classification. SVM only needs a few features and a small number of samples to have good performance, but it is difficult to implement for large-scale training samples.

LSTM has the function of mining time dimension and memory, and a few works [9, 25, 31] use this model. It is simple to implement, but its network is deep and computation-intensive. The works [23, 31, 34, 42, 44, 48] based on CNN have achieved good accuracy. CNN makes maximum use of local information of

Table 1. Public datasets.

Name	Collector	Types	Description	Ref
ULg Multimodality Drowsiness Database	the Laboratory for Signal and Image Exploitation (INTELSIG)	Physiolo-gical state	The database has various types of data related to sleepiness (signals, images, etc.). The purpose is to help researchers conduct experiments in the field of drowsiness monitoring [40] and develop and evaluate systems (ie algorithms) [40].	[39]
UAH DriveSet	E. Romera, L.M. Bergasa and R. Arroyo	Vehicle state	The database records 6 different drivers and vehicles showing 3 different behaviors (normal, drowsy, and aggressive) on two different roads (freeways and auxiliary roads). Video recording is more than 500 minutes of natural driving [41].	[3]
NTHU	National Tsing Hua University	Face state	The datasets recorded 36 testers of different races driving videos under different day and night simulated driving conditions with and without glasses. This datasets contain normal, drowsy, talking and yawning facial data in many different scenarios [22].	[22, 23, 32, 42–47]
YawDD	the University of Ottawa, Canada	Face state	The data set is videos taken from two different angles. It is taken by a camera installed on the dashboard of the car and a camera installed under the front and rear view mirrors of the car. There are drivers of different genders in the video, including drivers with and without glasses, smiling drivers, yawning drivers, sleepy drivers, and drivers looking around [39]	[32, 48–51]
CelebA	Multimedia Laboratory, The Chinese University of Hong Kong	Face state	This data set is a large-scale data set focusing on face attributes, including more than 200K face pictures, each with 40 attribute annotations. The images in this dataset have large pose changes and background clutter in different scenarios [52].	[48]
FDDB	the University of Massachusetts, Amherst	Face state	The data set is composed of 2,845 color and grayscale images, and 5171 images of human faces are included in the period. The images in the dataset provide a wide range of difficulties, including obstacles, problematic poses, low resolution, and out-of-focus faces [49].	[49]

images, but its disadvantages are that it requires a large number of sample data, slow training depth, and high-performance equipment.

5 Conclusion

In this paper, we review the research of fatigue driving detection systems and classify the fatigue detection methods currently used. The detection method based on the driver's physiological characteristics has high accuracy, but it will interfere with the drivers. Vehicle feature-based fatigue detection methods have low accuracy and complexity, and require expensive infrastructure. The fatigue detection method based on driver behavior is simple to operate and the most cost-effective, but it is easily affected by lighting, the driver's sitting posture, whether to wear glasses, etc. The results of the method based on multi-feature information fusion are relatively reliable, but the real-time performance is poor. These detection methods all have certain limitations. They have their own advantages and disadvantages in terms of accuracy and reliability of results, real-time performance, and ease of operation, which need to be weighed by researchers. In addition, for the selection of appropriate classifiers, researchers also need to choose according to the system objectives.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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