Driver Distraction From the EEG Perspective: A Review

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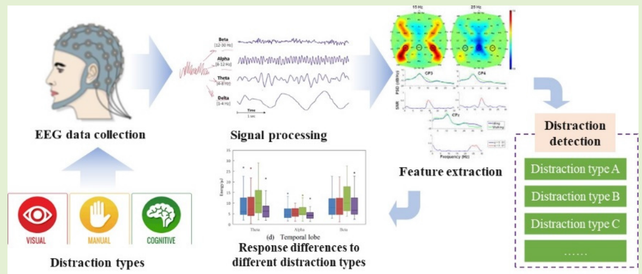
***Abstract*—A large proportion of car accidents are caused by distracted drivers. Thus, comprehensive analysis and understanding on driver distraction is essential for traffic safety improvement. Driver distraction can be revealed from their facial expression in images. However, this is easily affected by complex light distribution on faces or by low illumination during nighttime. Differently, drivers' physiological signals, such as electroencephalography (EEG), have been convinced to be one of the most reliable and direct tools for driver distraction studies, either for deeper understanding on driver distraction or for effective detection of driver distraction. Therefore, this article comprehensively reviews multiple aspects of driver distraction from the EEG perspective. First, the research progress on distracted driving is reviewed from three aspects: the definition of distraction, the types of distraction, and the main datasets of distracted driving. Second, computer signal processing is summarized into four aspects: signal acquisition, signal pretreatment, EEG main frequency bands, and EEG characteristics, and analyzed in turn. Third, the variation trends of EEG frequency bands under different distraction types were analyzed and compared. Fourth, the methods of feature extraction and detection of EEG in distracted driving are reviewed from the perspective of methodology. Finally, a new distraction detection method based on EEG integration with other physiological signals is summarized, and future development trends and technical challenges are prospected.**



***Index Terms*—Classifier, distraction detection, driving, electroencephalogram (EEG), feature extraction, preprocessing.**

I. Introduction

DISTRACTION refers to a cognitive state in which an individual's mental activities either fail to be fully directed and concentrated within the required timeframe or are completely separated and transferred to unrelated things from the primary task [1], [2]. In other words, distraction can be defined as the redirection of attention influenced by specific factors. With the integration of smartphones and infotainment systems in vehicular environment being prevail, the number of crashes and injuries caused by driver distraction is increasing year by year [3]. The National Highway Traffic Safety Administration (NHTSA) reports that 3522 people died due to distracted driving in 2021. Therefore, it is of critical importance to systematically analyze driver distraction for traffic safety improvement.

To date, according to the input signals, the studies on driver distraction can be categorized into three mainstreams: camera-based studies, driving performance-based studies, and physiological signal-based studies. However, camera-based studies and driving performance-based studies are less effective for distraction detection. Distraction performances recorded by cameras are easily affected by illumination (e.g., daytime and nighttime) and drivers' glass-wearing characteristics (e.g., vision-correction glasses and sunglasses). Driving performance measures are indirect indicators of driver distraction, which means that one of the specific measures may be invalid and related to other factors (e.g., fatigue) instead of distraction. For example, the frequently occurred lane departure or low steering wheel correction rate in driver distraction [4] also exist in fatigue driving. Different from camera-based

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studies and driving performance-based studies, physiological signal-based studies can more directly and effectively detect driving distraction using physiological signals with deep and systematic analysis.

Drivers' physiological signals mainly include electroencephalography (EEG), electromyogram (EMG), electrodermal activity (EDA), electrocardiogram (ECG), respiration pattern (RSP), electrooculogram (EOG), and heart rate variability (HRV). Among these various physiological signals, EEG is a powerful tool that has been widely used in various studies because it can provide high millisecond-level time resolution [5]. More importantly, in the current brain–computer interface research, the acquisition of EEG can also be selected noninvasively [6]. Given that many studies have reported the close relationship between driver distraction and EEG responses [7], [8], this article mainly focuses on presenting a picture on driver distraction from the EEG perspective, which aims to provide readers with a complete and general understanding on the related knowledge and technologies.

This article aims to provide a comprehensive review of EEG-based driver distraction detection techniques and their current advancements. The main contributions of this article can be summarized as follows.

1) We present a complete explanation of the definition of distraction, its types, and the existing mainstream distraction datasets.
2) We give the nonexpert reader a background on EEG and driving distraction and explain the purpose and significance of conducting this study.
3) We explain EEG, the process of acquiring EEG, and the relationship between EEG and distraction. EEG feature variations in distinct distractor states are also discussed.
4) We focus on feature extraction algorithms and classifier algorithms for EEG in distraction detection research and analyze the pros and cons of existing methods.
5) We identify various remaining challenges and future research directions to advance the development of EEG-based driver distraction detection.

We searched the following keywords on Google Scholar and the IEEE Xplore website to collect papers for this survey: (EEG AND Distraction AND Drive) or (EEG AND Distraction AND Detection). In total, 252 papers were collected. We then carefully identified the articles published between 2000 and 2023 that were closely related to EEG-based distraction studies. Some classical papers published before 2000 were also included, but the number was no more than five. After that, 190 papers were obtained. Subsequently, we manually selected the papers with more citations than the median of the filtered articles in the corresponding publication year and the papers with less citations but with novel contents. The final number of reviewed articles in this article is 115.

This article is organized as follows. In Sections II and III, the main types of distraction and the EEG datasets related to distraction are summarized. Section IV introduces in detail the EEG signal segment and EEG signal characteristics involved in data preprocessing and EEG signal processing. In Section V, the differences in the characteristics of brain wave segments under different types of distraction tasks are demonstrated and summarized. Section VI introduces the feature extraction algorithm of EEG in detail. Section VII summarizes EEG-based distraction detection methods. In Section VIII, the relevant distraction detection that incorporates EEG signals and other biological signals is summarized. Finally, the future development prospects of EEG distraction detection are prospected and summarized in Section IX. A more detailed overall structure of the article is shown in Fig. 1.

II. Distraction Categories

Driver distraction can be divided into four categories: visual distraction, auditory distraction, biomechanical (physical) distraction, and cognitive distraction [3]. The details of each category are introduced as follows.

A. Visual Distraction

Visual distraction is defined as the visual interference outside of the road conditions that shifts the driver's attention from driving. The main causes of visual distraction can be summarized as follows: rolling visual search behavior (e.g., observing vehicle dashboard) and static visual search behavior (e.g., observing mobile phone screen and billboard) [9]. Specifically, the rolling visual search behavior attracts the driver to continuously pay attention to and predict the changing information, while the static visual search behavior attracts the driver's attention through the information content provided by the relevant information source. One of the most common visual distractions caused by static visual search tasks is mobile phone distracted driving (MPDD). Related studies have shown that drivers who use mobile phones react to danger on average 50% slower than drivers who do not use mobile phones [10].

B. Auditory Distraction

Auditory distraction is defined as the interference caused by auditory signals that leads to the decreasing degree of driver's driving attention. Drivers' attention can be affected by lots of auditory factors, such as listening to music or news and talking to passengers. When drivers hear music or passengers' conversations, they tend to unconsciously pay attention to what they hear, such as the lyrics of the music and the topic of the passengers' conversation, which eventually leads to the distraction of the drivers. Neé et al. [11] reported that the most common distraction was listening to music, at a higher rate than talking to passengers in their study and other team studies. At present, related research around the world aims to develop accessory equipment to reduce or eliminate such auditory impacts on driver's attention. Son and Park [12] organized young and old subjects to perform visual and auditory dual tests, respectively. The auditory test was set as a delayed digital recall task, that is, the subjects were required to repeat a certain numerical sequence. Compared with the visual test, an auditory test is a kind of interference that is more difficult to detect. People who are distracted by hearing can hardly detect that they are in the process of auditory distraction.

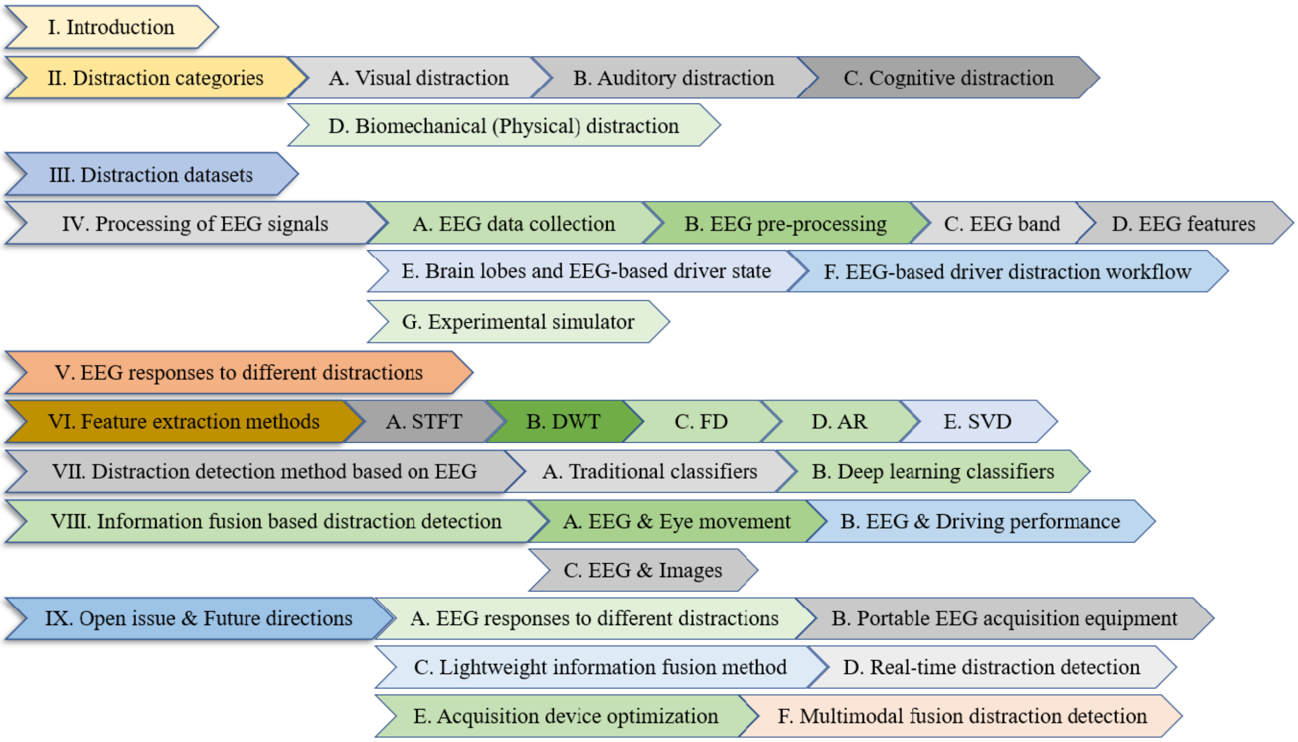

Fig. 1. Framework of driver distraction detection based on EEG and the development trend of integrating other physiological signals.

C. Cognitive Distraction

Cognitive distraction is defined as the spiritual interference resulted from drivers' thinking and imaging activities that endanger driving safety. A long-time driving with monotonous road conditions is prone to distraction of this type. Within a long-time driving, drivers would gradually lose attention as fatigue accumulates, which eventually leads to distraction [13]. Besides, cognitive distraction is one of the inducements of fatigue driving, such as continuous driving operation at night. Due to deficient attention resulting from sleepiness or biological disorder, fatigue driving leads to a great negative effect on driving safety [14]. Mishra et al. [15] pointed out the subtle influence of external interference on cognitive distraction and described three new cognitive training approaches. Given that cognitive distraction usually occurs unconsciously, it is necessary to keep drivers awake with external assistance for traffic safety.

D. Biomechanical (Physical) Distraction

Biomechanical distraction is defined as the interference that forces driver to manage it immediately and abandon driving operation. Biomechanical distraction usually happens in a sudden situation. For example, driver has to reset the rearview mirror when it is knocked askew in an accidental collision. In addition, biomechanical distraction also involves in-vehicle operations related to nondriving parts, such as adjusting the radio button, adjusting the air conditioning button, and operating the wiper. In a previous study, Li et al. [16] set biomechanical secondary tasks (i.e., mobile phone manipulation task, clock task, and two-back task) under the primary driving tasks and proved that distracted driving can be induced by such activities. Therefore, considering that biomechanical distraction is usually induced in emergencies, an intelligent and sound driving scheme that copes with different driving situations should be developed.

III. Distraction Datasets

Since the distraction studies began, many research teams have managed experiments to build datasets for further research. The main datasets in recent years are shown in Table I.

To assess the suitability of the recent research using prefrontal EEG to detect fatigue and distraction of train drivers, Fan et al. [17] constructed a unique dataset. There were totally seven experienced train drivers participating in the experiment. Each participant was required to drive in a simulated train-driving environment with two EEG electrodes on foreheads to collect EEG signals. Participants were asked to complete a simulated train driving experiment with three different tasks.

To explore how distraction differs in natural and laboratory settings, Kaushik et al. [18] conducted EEG datasets with 24 participants. There were 24 participants involved in experiments to investigate the relationship between difficulty of debate topics and neural responses as well as distraction degrees. There were totally 46 debates, including 23 easy debates and 23 difficult debates. In each experiment, participants were assigned a specific debate topic and asked to debate for either 10 min (easy debate) or 15 min (difficult debate). Preprocessed EEG data can be downloaded from: https:// unishare. nl/ index. php /s/ 1UYBg oG7tF 2xfqG.

To bring brain–computer interface technology into daily life, Brandl et al. [19] systematically studied the performance of

TABLE I
MOST INFLUENTIAL EEG-BASED DISTRACTION DATASET IN RECENT YEARS

Reference	Number of participants	Year	Number of channels	Type of distraction	Test environment	
					Virtual environment	Real environment
[17]	7	2022	2	Cognitive distraction	√	
[18]	24	2022	32	Cognitive distraction		√
[19]	16	2016	63	Cognitive distraction	√	
[20]	17	2021	8	Visual and auditory distraction		√
[21]	8	2020	35	Cognitive distraction	√	

brain–computer interface under simulated out-of-lab interferences. There were totally 16 participants. Each participant was required to perform the primary moving image task and one of six different secondary distraction tasks. The EEG data were collected in the procedure of experiments.

Apicella et al. [20] proposed an inattentiveness detection method to address patients' inattentiveness problems during rehabilitation training. The datasets used in the experiment were obtained by collecting eight-channel EEG signals from 17 participants. A total of 4590 epochs composed of eight channels of 512 samples were collected in the experiment.

As EEG is still of limited applicability in identifying cognitive distraction while driving, Schneiders et al. [21] proposed a machine learning framework with EEG inputs to detect cognitive distraction of drivers. To collect EEG data for the proposed framework, eight participants were involved to construct EEG datasets in which data could reflect their EEG characteristics under cognitive distraction.

IV. PROCESSING OF EEG SIGNALS

A. EEG Data Collection

A typical EEG signal acquisition system mainly includes a signal acquisition device, an amplifier, and a data storage device, as shown in Fig. 2. The signal acquisition device is a hardware device, which mainly collects human EEG signal electrode EEG cap. The amplifier serves to amplify the faint EEG signals, rendering its characteristics more discernible and facilitating subsequent processing. Finally, the data can be stored in the data storage device.

At present, the mainstream collection tools are divided into external type and implanted type. The main forms of external collection equipment include traditional electrode caps and headbands. Both dry electrodes and wet electrodes are mainly used in electrode map. The wet electrode is made of silver or silver chloride material. By using wet electrode, although the collected signal quality is high, the electrolytic gel needs to be coated every time. Though the process is tedious, it is suitable for laboratories. The dry electrode uses stainless steel as the conductor, and the quality of the collected signal is lower than that of the wet electrode. However, it is convenient to use and suitable for real driving conditions. Their electrode positions are usually based on 10–20 international system electrode positioning standards that

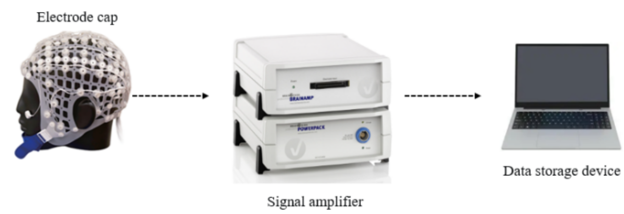

Fig. 2. EEG acquisition system.

were proposed in 1958 [22] (see Fig. 3). In addition, the electrode cap is also divided into wired connection and wireless connection. Due to cable oscillation, wired connections are prone to be influenced by motion artifacts during the acquisition process, while wireless connections face issues, such as electrical noise and unstable signal connections during wireless transmission. Most implantable devices used in laboratories include implantable lead components, implantable telemetry units, and external personal advisory devices [23]. Since data can be collected more directly, implantable devices can get data with fewer artifacts. However, the technology of implantable devices is not perfect as it is more expensive and requires a surgical operation that would likely to cause rejection or infection. Therefore, the external EEG acquisition equipment is the most commonly used in the current laboratory.

The main function of the amplifier is to collect, amplify, and convert analog electrical signals from electrode cap sensors into digital signals, which can be processed by computers. After a certain range of bandwidth is selected, the amplifier can obtain the amplified signals of the corresponding frequency range. A larger bandwidth can cover a wider frequency range of signals but induce more noise as well. Currently, a prominent product in the market is the BrainAmp amplifier, manufactured by the German company Brain Products [24].

The data storage device is used to save experimental data and provide a convenient way for data loading. Common data storage devices include laptops and microprocessors, which are easy to carry.

B. EEG Preprocessing and Artifact Removal

Recording EEG signals with multiple electrodes makes data with a high time resolution, which results in artifacts because

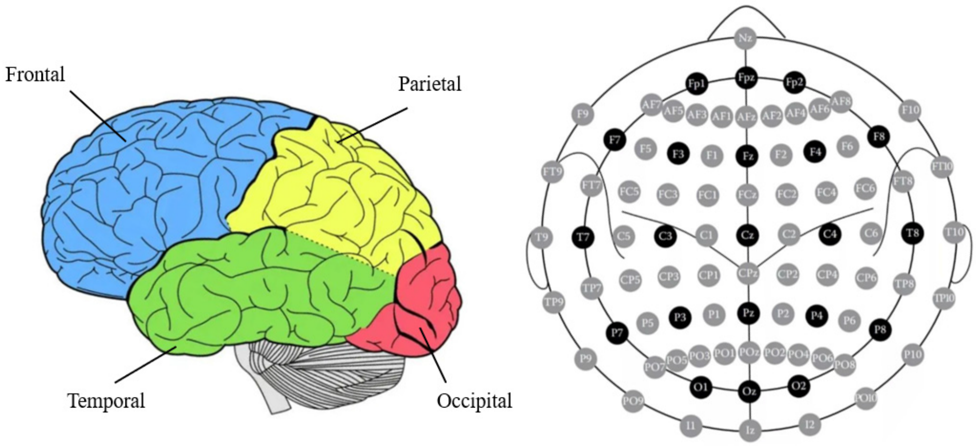

Fig. 3. EEG 10–20 international system.

of noise pollution in the signal amplification process. Artifacts can be understood as "fake" EEG signals hidden in "real" EEG signals. In other words, irrelevant signals from other signal sources are mixed into EEG signals. The source of artifacts can be physiological and nonphysiological. Specifically, physiological artifacts mainly result from eye movement, blinking, heart activity, and muscle activity, while nonphysiological artifacts usually occur because of loose contact between the measuring instrument and the human skin, electrode defects, line noise, and high electrode impedance [25].

The purpose of signal preprocessing is to remove artifacts. Researchers employ algorithms to filter, segment the collected EEG data, and adjust the baseline. Commonly used data processing approaches that removing extreme values and rereferencing potential difference of electrodes are also included in this procedure, and finally, artifacts will be diminished. This process is called preprocessing of EEG signals. Recent published artifact removal techniques are evolving mainly through improving existing algorithms, combining multiple methods, and automating the removal process. These techniques could be divided into two categories: using reference channels to estimate artificial signals and decomposing EEG signals into other domains. Approaches server as compositions of these techniques could be regression, blind source separation (BSS), empirical mode decomposition (EMD), wavelet transform algorithms, and their hybrid methods.

1) Regression Analysis: In statistics, regression analysis refers to a statistical analysis method that investigates the quantitative relationship between two or more variables. In the context of big data analysis, regression analysis is a predictive modeling technique to study the relationship between dependent variables and independent variables. This technique is commonly used for predictive analysis, time series modeling, and discovery of causal relationships between variables.

When applying regression analysis in artifact removal, artifacts can be regarded as independent variables and EEG signals as dependent variables. The assumption of regression analysis is that the measured EEG signal is composed of pure EEG signal and pseudo-brain signal. When the estimated "pure EEG signal" is getting closer to the ground truth by adjusting the weighting factor, the result will get closer to the de-artifacted EEG signal that the staff needs. As shown in the following:

$$\mathrm{EEG}_{\mathrm{measure}} = \mathrm{EEG}_{\mathrm{correct}} + p \times \mathrm{EOG} \tag{1}$$

where $\mathrm{EEG}_{\mathrm{measure}}$ is the collected EEG signal, $\mathrm{EEG}_{\mathrm{correct}}$ is the ground-truth pure EEG signal, EOG is the ocular signal, and p is the weighted factor [26].

2) Independent Component Analysis (ICA): ICA is an algorithm for multivariate signal processing. According to the above categories, ICA is a BSS algorithm. The two main assumptions of ICA are as follows. First, the mixed signal is composed of several statistically independent components. Second, the relationship between the mixed signal and each independent component is linear. Therefore, the ICA equation is

$$X_{[n\times k]} = W_{[n\times m]} \times S_{[m\times k]} \tag{2}$$
$$S_{[n\times k]} = A_{[m\times n]} \times X_{[n\times k]} \tag{3}$$

where (2) is the reconstruction formula and (3) is the decomposition function. In these equations, X is the acquired EEG signal matrix with n channels and k samples. S is the independent component matrix with user-defined m components. W is the transformation matrix and A is the pseudoinverse of the W matrix. ICA was first applied to biomedical time series analysis by Makeig et al. [27]. The report shows the separation of eye movements from EEG phenomena. In the process of studying human cognition under specific driving tasks, Lin et al. [28] calculated the gradient of ICA component scalp map of the same subject at different periods and grouped them according to the highest correlation of common electrode gradient.

3) Canonical Correlation Analysis (CCA): CCA is a kind of BSS algorithm, which is used to find the greatest correlation between two multivariate datasets. Specifically, suppose that X and Y are two sets of datasets, and the CCA algorithm tries to find vectors a_x and a_y as

$$\max_{a_x a_y} \rho\left(a_x X, a_y Y\right) = \frac{E\left[a_x X a_y Y\right]}{\sqrt{E\left[(a_x X)^2\right] E\left[\left(a_y Y\right)^2\right]}} \tag{4}$$

where ρ is the correlation factor between $a_x X$ and $a_y Y$. By taking the derivative of (4), the maximum correlation factor yields:

$$\begin{cases} C_{xx}^{-1} C_{xy} C_{yy}^{-1} C_{yx} a_x = \rho^2 a_x \\ C_{yy}^{-1} C_{yx} C_{xx}^{-1} C_{xy} a_y = \rho^2 a_y \end{cases} \tag{5}$$

where C_{xx} and C_{yy} are the autocovariance of X and Y, respectively, and C_{xy} and C_{yx} are the cross-covariance between X and Y, respectively. De Clercq et al. [29] first applied the CCA algorithm to EEG to remove muscle artifacts, and the results were superior to those obtained by ICA in similar experiments. Traditional CCA algorithms need to manually mark artifacts, but some researchers have made improvement to the CCA algorithms to enable automatically mark [30] and process artifacts in real time [31].

4) Wavelet Transform (WT): Wavelet transform can be regarded as another form of Fourier transform, and it applies a specific waveform to decompose the signal. Wavelet transform can be divided into continuous wavelet transform and discrete wavelet transform (DWT). CWT is a signal processing technique for time–frequency analysis of nonstationary signals, while DWT is usually used for signal denoising and artifact removal. In DWT analysis, the input signal is decomposed into detail and approximate information with a high-pass and a low-pass filter, respectively, as follows:

$$\begin{cases} y_{\text{low}}[n] = x[n] \times g[n] \\ y_{\text{high}}[n] = x[n] \times h[n] \end{cases} \tag{6}$$

where $x[n]$ is the raw signal, $g[n]$ is the low-pass filter, and $h[n]$ is the high-pass filter. Also, $y_{\text{low}}[n]$ and $y_{\text{high}}[n]$ are approximate information under low- and high-pass filters. For wavelet transform, the choice of waveform and decomposition level is the key to the artifact removal effect. However, due to different experimental purposes and conditions, there is no specific benchmark for waveform selection and decomposition level.

C. EEG Frequency Bands

The reason why EEG signals can reflect a person's mental activity and brain state is that some features of the EEG signals will produce certain changes in response to changes in people's states. A significant feature is the frequency of brain electricity. EEG signal is usually divided into five frequency bands, and different frequency bands can reflect the different activity states of the brain. Many studies of driver distraction have shown that changes in theta, alpha, and beta frequency bands are the best indicators of a driver's cognitive level. EEG frequency band is the most commonly used feature in EEG analysis, and the characteristics and meanings of each frequency band are shown in Table II.

D. EEG Features

Since EEG signals are nonstationary and the collected signals are usually high-dimensional, it is necessary to extract features for filtering and dimensionality reduction. Commonly used EEG features can be mainly divided into the following categories: time-domain, frequency-domain, time–frequency domain, nonlinear, entropy, and space-domain features. Each category has several specific features and the job of feature extraction is to find these features. These features are concrete data for analyzing the brain state of the subjects, which are of great significance to the future work. The main EEG features are summarized in Table III.

1) Time-Domain Features:

a) Event-related potentials: Event-related potentials (ERPs) are potentials produced by the brain that are related to specific internal or external events. They can be recorded noninvasively from almost any group of participants and can provide information about a wide range of cognitive and emotional processes. Therefore, ERP technology has become a common tool in many fields of psychology research, and researchers must be able to understand and evaluate ERP research in the literature. Frantzidis et al. [32] used the amplitude and latency of ERPs (P100, N100, N200, P200, P300) as features in the study.

b) Statistics of signal: Statistical characteristics are commonly used in statistics to reflect the statistical significance of a batch of data, such as the degree of dispersion. Many of the statistical data signals can be used as EEG features, such as mean value, maximum value, minimum value, energy, median, variance, standard deviation, skewness, and kurtosis [33].

c) Hjorth parameters: Hjorth developed the following features of a time series, which were used in EEG studies. Activity, mobility, and complexity [34] are the first three derivatives of the signal and the most-used Hjorth parameters. These three parameters will collectively characterize EEG patterns in terms of amplitude, time scale, and complexity. The three parameter values referring to each epoch can be printed online at the end of the epoch or transferred to automatically calculate averages, variables, and so on.

Activity gives a measure of the squared standard deviation of the amplitude, sometimes called variance or mean power. Mobility gives the standard deviation of the slope in terms of the standard deviation of the amplitude, which is expressed as the ratio per time unit and can also be understood as the average frequency. Complexity gives a measure of excessive detail about the "softest" curve shape, the sine wave, which corresponds to unity and is expressed as the number of standard slopes actually produced in the average time required to produce a standard amplitude given by mobility.

d) Nonstationary index (NSI): NSI is a complexity measure that divides the signal into small parts and estimates the change in the local mean. As early as 2000, Hausdorff et al. [35] adopted NSI as one of the kinetic indicators of gait rhythm changes in patients with ALS. Kroupi et al. [53] used NSI as a measure of complexity, which is the object of feature extraction, by analyzing changes in local average over time. They divide the normalized signal into small parts and calculate the average of each part. NSI is defined as the standard

TABLE II
BAND POWER AND THEIR CORRESPONDING STAGES OF DISTRACTION

Band type	Frequency range (Hz)	Trends in distraction	Distraction or attention state
δ	0.1-3 Hz	Reduction	Severe distraction or lethargy
θ	4-7 Hz	Significant reduction	Increased distraction
α	8-12 Hz	Significant reduction	Start to get distracted
β	12.5-28 Hz	No obvious change	Normal attention level
γ	29-50 Hz	No obvious change	Alert and excited

deviation of all means, where a higher index value indicates more inconsistent local means.

e) Zero-crossing rate (ZCR): The ZCR is a characteristic parameter of the time signal, which represents the number of times the signal passes through the zero point (from positive to negative or from negative to positive) in each frame. As a typical time signal, the EEG signal is often used as a parameter for feature extraction. Michielli et al. [36] extracted ZCR as a feature when conducting a study to classify the study stage.

f) Normalized length density (NLD): Kalauzi et al. [37] introduced NLD to estimate the fractal dimension (FD) for a very short period of time when evaluating the complexity of a 1-D sampled signal. The principle is as follows:

$$\mathrm{NLD} = \frac{1}{N}\sum_{i=2}^{N} \left| y_n(i) - y_n(i-1) \right| \tag{7}$$

where $y_n(i)$ represents the ith signal sample after amplitude normalization and $y_n(i-1)$ represents the previous signal sample of $y_n(i)$. N represents the number of samples. When $N < 100$, NLD is more accurate to extract FD(t). It can be used for physiological signals such as transient artifacts where FD is expected to change suddenly. Finally, their results also show that the current variation of the signal FD is more accurate than the Higuchi method or the continuous difference method.

g) K-complex: Sleep macrostructure refers to five main stages: W, N1, N2, N3, and REM. Among them, the K-complex wave is the characteristic waveform that appears in the N2 stage. As a common feature extraction parameter, its extraction method optimization is a mainstream research direction. Oliveira et al. [38] proposed a new method called MT-KCD to automatically detect KC in human sleep EEG.

h) Event-related desynchronization/synchronization (ERD/ERS): ERD/ERS analysis allows the evaluation of power changes in specific frequency bands with temporal resolution comparable to ERP, which combines the advantages of spectral power analysis and ERP analysis. Bekkedal et al. [39] delineated responses to affective vocalizations by measuring frontal theta event-related synchronization. Due to the advantages of the ERD/ERS signature, they used the analysis of this signature as a method to detect the instinctive responses of the brain that occur during emotional communication.

i) Higher order crossing-based (HOC-based): HOC is a computational method that combines zero-crossing counting and linear operations (filters) [40]. The principle can be seen as an iterative process: first apply a filter to a time series and calculate the number of zero crossings after the filtering ends, and then apply the filter to the original time series and calculate the number of zero crossings after the filtering ends. When a specific filter sequence is applied to a time series, the corresponding HOC sequence is obtained. These HOC sequences used for classification are HOC-based features. Petrantonakis and Hadjileontiadis [54] proposed a feature extraction technique based on emotional arousal and EEG. They used HOC analysis for feature extraction, named HOC-emotion classifier (HOC-EC), revealing the potential of a robust EEG emotion recognition method.

2) Frequency-Domain Features:

a) Band power: In EEG distraction recognition, the most commonly used features are power features in different frequency bands. The band powers are usually used to describe the level of brain activities in the corresponding brain regions. One limitation of this feature is that it is assumed that the signal is stable in the data collection phase. Different bands represent different meanings. Therefore, driver's attention state can be detected by observing the change of amplitude of different bands or the change of band ratio size.

b) Higher order spectra (HOS): Higher order spectrum is also called multispectrum, which refers to the spectrum of multiple frequencies. It is a higher order statistic. High-order spectrum can solve problems that the power spectrum cannot. When the phase information is as important as the amplitude information or even the phase information is more important, the correlation domain method can only accurately describe the minimum phase signal equivalent to the power spectrum domain but cannot provide the correct phase information. However, the higher order spectrum can provide more information. Second-order and other higher order spectra of HOS can identify nonlinear couplings between phases. It means that HOS can identify each component of a certain frequency factor consisting of two (or more) frequency factors. Hosseini et al. [44] proposed an HOS-based emotional stress recognition system. They used the sum of bispectral magnitudes, the sum of squares of bispectral magnitudes, the sum of bicoherence magnitudes, the sum of squares of bicoherent magnitudes, and the other three quantities as features for feature extraction.

3) Time–Frequency Domain Features:

a) Hilbert–Huang spectrum (HHS): The concept of Hilbert spectrum and Hilbert spectrum analysis method was proposed

TABLE III
SUMMARY OF EEG FEATURES

Feature type	Feature name	Feature substance	Reference
Time domain features	ERP	A small electric voltage change that can be measured by EEG	[32]
	Statistics of signal	Numerical indicators reflecting the mathematical properties of signals	[33]
	Hjorth parameters	Features that are based on the variance of the derivatives of the EEG signal	[34]
	NSI	Index for evaluating the consistency of the local mean over time	[35]
	ZCR	The rate at which the sign of a signal changes	[36]
	NLD	An index used to capture the self-similarity of EEG signals and explore their relationship to the dimensions of valence, arousal and liking	[37]
	K-complex	A characteristic waveform of EEG signals that can be used as a marker of non-REM sleep stage 2	[38]
	ERD/ERS	Power decrease/increase in specific frequency bands after stimulation	[39]
	HOC-based	Specific time series calculated by HOC	[40]
Frequency domain features	δ, θ, α, β, γ	Different frequency bands of EEG signals	-
	β/α	A ratio that represents the ratio of fast-wave and slow-wave activities. The larger the value, the higher the alertness level, that is, the more concentrated the attention.	[41]
	θ/α	A ratio that represents the ratio of slow-wave and fast-wave activity, with higher values indicating lower levels of attention.	[41]
	$(\theta+\alpha)/\beta$, θ/β, $(\theta+\alpha)/(\alpha+\beta)$	A ratio that more represents the ratio of slow-wave and fast-wave activity, with higher values indicating lower levels of attention.	[42]
	γ/δ, $(\gamma+\beta)/(\delta+\alpha)$	A ratio representing fast-wave and slow-wave activity, with higher values indicating higher levels of attention.	[43]
	HOS	Spectrogram reflecting the interaction between different waves	[44]
Time-frequency domain features	HHS-based	A time-frequency feature vector obtained after empirical mode decomposition (EMD) and Hilbert spectrum (HHS) analysis.	[45]
	Wavelet coefficients	The features extracted by wavelet transform	[46]
	Brain connectivity estimators	The features of mental stress were reflected by brain connectivity estimation method	[47]
Nonlinear features	HFD	Proposed by Higuchi, a fractal dimension obtained by a method estimated directly in the time domain without reconstructing the singular attractor.	[48]
	PFD	Proposed by Petrosian, a fractal dimension that is quickly computed by converting a time series into a binary series.	[49]
	KFD	Proposed by Katz, a fractal dimension derived directly from a waveform without the preprocessing step of creating a binary sequence.	[50]
Entropy features	HSE	It measures the average information contained in the probability distribution function.	[51], [52]
	HLE	It can derive continuous families of mutual information measures.	[51], [52]
	HRE	It can characterize the nonlinear dynamic of EEG signal and describe the electrophysiological behavior of brain region.	[51], [52]
Space domain features	Spatial feature vector	A feature matrix that reflects the maximum variance difference between distracted categories.	[55]

by Norden E. Huang et al., in 1988, namely, Hilbert–Huang transform (HHT). The HHT process mainly includes two parts: EMD and Hilbert spectrum (HHS) analysis. It is used to obtain the instantaneous frequency components with actual physical meaning in the signal for time–frequency analysis. Hadjidimitriou and Hadjileontiadis [45] compared the effects of STFT-based spectrogram (SPG), Zhao–Atlas–Marks (ZAM) distribution, and Hilbert–Huang spectrogram (HHS) on EEG characteristics of subjects' musical preferences. The results show that the feature extraction vector based on HHS is more robust to noise damage than the other two feature vectors.

b) Wavelet coefficients: Wavelet transform is a modern spectrum analysis tool. It can not only examine the frequency-domain characteristics of local time-domain processes but also examine the time-domain characteristics of local frequency-domain processes. Thus, it is easy to handle nonstationary processes. Prabhakar et al. [46] used DWT and continuous wavelet transform to process the time–frequency component coefficients of the original data of pupil dilation, head yaw, and EEG. The component coefficients here are one of the wavelet coefficients.

c) Brain connectivity estimators: The brain connectivity estimator can describe brain organization and connectivity pattern and then reflect driver's distraction status. Brain connectivity estimator is an integration of time-domain features and frequency-domain features. It can be mainly divided into three categories: structural connectivity, functional brain connectivity, and effective brain connectivity. The functional brain connectivity estimators cover includes time-domain features, such as Granger–Geweke causal connectivity (GGC), and frequency-domain features, such as directed transfer function (DTF), partial directed coherence (PDC), and generalized PDC (GPDC). Perera et al. [47] proposed an EEG-based driver distraction classification method with brain connectivity networks. They calculated connectivity matrices with four brain connectivity estimators, GGC, DTF, PDC, and GPDC, and used these connectivity matrices as features to train a support vector machine (SVM) to classify distracted and nondistracted driving tasks.

4) Nonlinear Features: FD is known as the fractal theory of natural geometry. It is a new branch of modern mathematics, but its essence is a new world view and methodology. FD reflects the effectiveness of the space occupied by complex shapes, and it is a measure of the irregularity of complex shapes. It is cross-combined with the chaos theory of dynamical system and complements each other. FD is a commonly used method to measure complexity. It can be calculated by using the Sevcik method, fractal Brownian motion, Box counting, or Higuchi algorithm.

5) Entropy (EN) Features: Entropy is a measure of the randomness of signal, and it represents the disorder of chaotic system. By using the nonlinear behavior of entropy to measure signal complexity, it becomes feasible to effectively describe and distinguish EEG signals that are nonstationary. At present, mainstream entropy features, such as Shannon entropy, log-energy entropy, and Renyi entropy, have been used by some research teams to measure the spectral complexity of time series data [51], [52]. Therefore, entropy features have a significant ability to characterize the complexity of EEG signals. Assuming that in a time series, the power level of the ith frequency component is p_i, for a given dataset of length N and the mean, the corresponding characteristics of Shannon entropy (HSE), log-energy entropy (HLE), and Renyi entropy (HRE) can be expressed as

$$H_{\mathrm{SE}} = -\sum_{i=1}^{N} p_i^2 \times \log_2\left(p_i^2\right) \tag{8}$$

$$H_{\mathrm{LE}} = \sum_{i=1}^{N} \log_2\left(p_i^2\right) \tag{9}$$

$$H_{\mathrm{RE}} = \frac{1}{1-\alpha}\log\sum_{i=1}^{N}(p_i)^{\alpha}. \tag{10}$$

The HRE is of order α where $\alpha > 0$ and $\alpha \neq 1$. If α is equal to 2, both sub-Gaussian and super-Gaussian components are equally weighted. In addition, if $\alpha = 2$, the measurement is called quadratic Renyi entropy, which is given by

$$H_{\mathrm{RE}} = -\log\sum_{i=1}^{N}(p_i)^2. \tag{11}$$

6) Space-Domain Features: The spatial feature vector is the most commonly used spatial domain feature, which reflects the maximum difference in variance between two EEG signal classes. Its calculation principle is to use the diagonalization of the matrix to find a set of optimal spatial filters for projection, so as to maximize the difference in variance values between the two types of signals. Spatial feature vectors are generally used for binary classification distraction detection tasks and are suitable for multichannel EEG data. Zhang et al. [55] combined DWT with common spatial pattern (CSP) to propose a new wavelet spatial domain feature (WSDF) for decoding olfactory EEG signals. They proved that the proposed WSDF can be used for related classification tasks.

E. Connection Between Brain Lobes and EEG-Based Driver State

The space-domain features are mainly from key brain regions that are responsible for detecting driver alertness, drowsiness, or distraction. In the study of driver status, the frontal lobe, temporal lobe, parietal lobe, and occipital lobe are the main research areas (see Fig. 3). These four regions represent the driver's execution ability, memory ability, perception ability, and visual function. These four areas can be covered by the electrode positions of the 10–20 international system standards, which can fully reflect the driver's status.

Due to different types of distraction, the spatial features of these four regions may exhibit differences during distraction detection experiments. Lin et al. [56] designed a dual-task event that included unexpected vehicle deviations and mathematical problems to explore the performance of the brain lobes during cognitive distraction. Finally, it was found that the frontal lobe region showed an increase in θ wave energy. Li et al. [7] used clock tasks, two-back tasks, and navigation tasks as auxiliary tasks to explore the brain dynamics of the frontal, parietal, occipital, and temporal lobes in simulation experiments. The results showed that θ wave energy increased in the frontal lobe during cognitive distraction and α wave activity decreased in the parietal and occipital lobes during visual and auditory distraction.

F. EEG-Based Driver Distraction Workflow

A typical EEG-based driver distraction analysis workflow can be described as follows. First, the raw EEG data are gathered and preprocessed. Feature extraction and data dimensionality reduction are then carried out. The next step is using the trend of loss function changes, doing data training to optimize the model, and generating the optimal model. In the end, the best model is imported. The experimental data are classified by using a classifier and the distraction

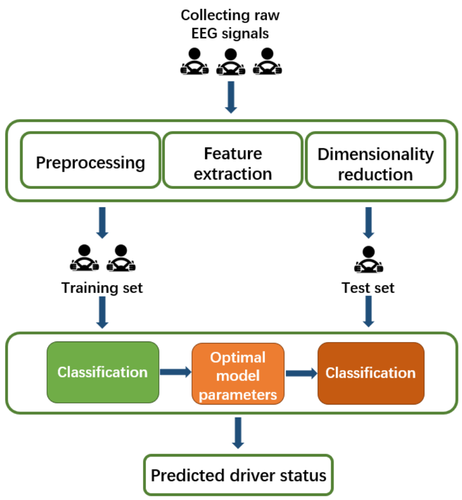

Fig. 4. Workflow of the EEG-based driver distraction.

state is evaluated. A flowchart of a typical EEG-based driver distraction detection is presented in Fig. 4.

The purpose of signal preprocessing is to reduce noise and remove artifacts, thereby improving the quality of experimental data. Feature extraction provides features, such as time and frequency for model development. Classifiers establish mathematical models or neural network models to perform tasks, such as distraction detection.

G. Experimental Simulator

The concept of simulation can be defined as the simulation of specific behaviors through a universal simulation system. Virtual simulation can develop and evaluate new systems with low investment in a short period of time. Therefore, it is widely used in driver distraction detection experiments. The most common laboratory simulators are desktop simulators, fixed-based simulators, and motion-based simulators.

1) Desktop Simulators: Desktop simulators typically consist of a PC, several monitors or screens, a simple cabin, and seats with limited mobility [57]. When subjects use this simulator for distraction experiments, they are required to wear collection tools to collect physiological signals such as EEG and EMG. Although the desktop simulator is low cost, its effectiveness of immersion is very low. In addition, its simulation fidelity mainly depends on the quality of visual cues.

2) Fixed-Based Simulators: A fixed-based experimental simulator typically includes several large projection screens, a complete vehicle cockpit, a PC, a fixed base, and speakers. Compared to desktop-based simulators, fixed-based simulators provide a more immersive simulated driving environment. Speakers and other devices have added experimental types related to distraction detection, which is conducive to collecting EEG data of different types of distraction.

3) Motion-Based Simulators: The composition of the motion-based simulators is similar to that of the fixed-based simulators, except that the experimental simulator has a moving base with several degrees of freedom. The base is used to place the cockpit. During the experiment, the moving base can generate vibration when vehicles pass through nonstationary road sections in the simulation scene. This can further enhance the subjects' immersion and collect higher quality EEG data [58]. Currently, one of the highest fidelity motion-based simulators internationally is the NADS-1 simulator. It can move, tilt, and rotate on the bay floor to simulate the movement of a car on the road, while the driver is surrounded by a virtual environment projected 360° on the inner wall of the dome.

V. EEG Responses to Different Distractions

A. Differences of EEG in Different Frequency Bands Under Visual Distraction

Visual distraction mainly affects the middle- and low-frequency bands, and a significant change in the low-frequency band indicates that a driver is in a state of depression and boredom, leading to distraction. Brome et al. [59] analyzed and compared the effects on driver performance and attention allocation of three types of digital billboard advertisements: static (single image), transition (one static DBA replaced by another), and animation (short video). The results showed significant differences in the performance of the driver's theta and beta bands under the influence of the three DBAs. Pradeep Kumar et al. [60] used α and θ bands to analyze the fatigue state of drivers in EEG during simulated driving tasks. By sending messages to drivers' phones to distract their visual attention, significant differences between theta and alpha subbands appeared when drivers produced event analysis.

B. Differences of EEG in Different Frequency Bands Under Auditory Distraction

The auditory distraction task mainly affects the low-frequency bands. Sonnleitner et al. [61] designed a hearing aid experiment to explore the impact of auditory secondary tasks on the driver's mental state in the primary driving task. In the experiment, subjects were demanded to repeat the forced braking action on the nonpublic test track. Also, the classification method is used to study whether the α-spindle wave can predict the psychological state of the driver. Finally, it was found that the driver's braking reaction time and alpha spindle frequency were significantly increased under auditory-assisted driving compared with driving alone. This also shows that attention has shifted to auditory input, which leads to a delay in visual information processing.

C. Differences of EEG in Different Frequency Bands Under Cognitive Distraction

Cognitive distraction tasks mainly affect low- and mid-frequency bands of EEG signals, and mid-frequency bands such as beta typically indicate that a driver is engaged or alert, so a significant change in mid-band intensity can often indicate a change in a driver's mental state, potentially distracting. Almahasneh et al. [62] organized 42 subjects to participate in the experiment to study the impact of mathematical problems and decision-making problems on the cognitive state of the driver. Experimental results show that the mathematical task significantly affects the EEG amplitude, theta zone, the upper and lower alpha zones, and the upper beta zone of the right frontal lobe, while the effect is not significant in the left frontal lobe. Decision-making tasks have a significant impact on the left and right frontal hemispheres. The right hemisphere affects the lower and upper beta bands, and the left hemisphere affects the theta and upper alpha bands. Lin et al. [28] designed to combine mathematical tasks and vehicle deviation tasks and conduct research on changes in EEG signals.

D. Differences of EEG in Different Frequency Bands Under Biomechanics (Physical) Distraction

Biomechanical (physics) distraction mainly affects low-frequency bands. To detect driver distraction based on multimodal signals in real traffic, Zuo et al. [63] proposed a new framework based on multiscale entropy (MSE) in sliding windows and bidirectional long short-term memory network (BiLSTM). Before the MSE feature calculation, time–frequency analysis of the alpha frequency band is required. The experimental results showed that if attention shifts occur, alpha rhythmic activity in the parieto-occipital brain region increases. Sollins et al. [64] studied the effects of cell phones and touch MP3s on commercial truck drivers. The results showed that the driver's prefrontal theta level and parietal alpha level were significantly improved compared to the no-distraction case.

VI. Feature Extraction Methods

Feature extraction is a term in machine learning that extracts the desired information from redundant noisy signals [65]. Since EEG signals are nonstationary and are usually collected in a high-dimensional environment, feature extraction is necessary for filtering and dimensionality reduction. In the research of driver distraction based on EEG, according to the above EEG features, the feature extraction algorithm based on time domain, frequency domain, time–frequency domain, and space domain is used to obtain driver state characteristics. In this section, we introduce common EEG feature extraction methods and applications for driver distraction research and the current mainstream feature extraction methods are summarized in Table IV.

A. Short-Time Fourier Transform (STFT)

The short-time Fourier transform (STFT) is a mathematical transformation related to the Fourier transform, which is used to determine the frequency and phase of the sine wave in the local region of a time-varying signal. It divides the signal into equal-length parts and then applies the Fourier transform to each shorter signal. Alizadeh and Dehzangi [74] calculated the power spectral density (PSD) of the four main EEG frequency subbands and used the PSD function to represent the energy intensity as a function of frequency, showing the relationship between the strength and weakness of frequency changes. Finally, features based on STFT were extracted from each of the four signals to capture oscillations of various frequency subbands associated with brain processes. Pampu [66] investigated the effect of STFT configuration to determine how the parameters of STFT affect the spectral estimation of the mean and relative power of EEG signals in the β and γ bands.

B. Discrete Wavelet Transform (DWT)

DWT is a tool to transform time-domain signal into wavelet of different frequency bands. The decomposition tree of DWT consists of two filters in each stage: high-pass filter (Go) and low-pass filter (Ho). The signals are divided into different frequency bands and then downsampled. This sampling method precisely halves the length of the signal at each stage to improve frequency resolution. Vamsi et al. [67] proposed a new index to evaluate the sleepiness state of drivers. It is accomplished by using EEG combined with time–frequency analysis to quantify the sleepiness state of drivers. In the experiment, they used DTW for feature extraction and then applied the extracted features for rhythm distraction.

C. Fast Fourier Transform (FFT)

Fast Fourier transform (FFT) is a fast algorithm of discrete Fourier transform (DFT). It is obtained by improving the algorithm of DFT according to its odd, even, imaginary, and real characteristics. FFT is one of the most basic methods in time–frequency domain transform analysis and is often used in EEG feature extraction. Ben Dkhil et al. [68] calculated the absolute band power of EEG signals by performing FFT on time series signals and finally developed a method to automatically evaluate the sleepiness phase by analyzing EEG recordings.

D. Fractal Dimensions Algorithm (FD)

FD is a method to show the chaotic or fractal properties of a signal. FD is a statistical measure that shows how fractals fill the space at different scales. FD can easily provide us with the stability index and time scale corresponding to the characteristic frequency, even for a small amount of data. Since all FD estimation methods are not suitable for all types of data, it is sometimes necessary to use other common methods to characterize time series, such as Katz and Higuchi methods. Wijayanto et al. [69] proposed a fractal-based EEG seizure detection method. After decomposing the EEG signal into five subbands, they used FD to extract five features. Among them, the algorithm provided by Katz is used for signal identification. Using a fractal analysis-based complexity measurement technique, Harne [70] compared EEG signals before and after OM chanting. He used the Higuchi algorithm to calculate the time-domain FD.

E. Autoregressive (AR)

Autoregressive model (AR model) is a statistical method of processing time series, using the same variable, such as the previous periods of x, that is, x_1 to x_{t-1} to predict the performance of x_t in this period. Also, the AR model assumes a linear relationship among these variables. Although this model is developed from linear regression in regression analysis, instead of using x to predict y, it uses x to predict

TABLE IV
SUMMARY OF MAINSTREAM METHODS FOR FEATURE EXTRACTION

Reference	Method	Electrodes	Main work	Advantages	Drawbacks
[66]	STFT	32 channels	They investigated changes in power estimates for specific bands of EEG signals by adjusting STFT-related parameters.	Signals can be analyzed in both the time and frequency domains, and non-stationary signals can be analyzed.	The STFT cannot meet the requirements of the frequency of the unsteady signal change.
[67]	DWT	8 channels	They analyzed driving performance by comparing the relative wavelet packet energy in the parietal, occipital and temporal lobes of sleepy and normal subjects.	This method improves the frequency resolution by precisely halving the signal length at each stage.	DWT requires a large amount of computation, and if the dataset is large, it takes a long time to get the result.
[68]	FFT	14 channels	They applied fast Fourier transform to the collected EEG signals and obtained different bands of EEG signals by band-pass filtering.	Fast Fourier transform is more suitable for computing high complexity features.	FFT is deficient in distinguishing the degree of dispersion represented by features.
[69]	Katz algorithm (KFD)	100 channels	They examined changes in EEG signals to monitor normal, preeclamptic, and seizure status in epileptic patients.	Feature extraction can be done without a large number of features, and the calculation process is simplified.	The choice of fractal dimension will have a great impact on the experimental results.
[70]	Higuchi algorithm (HFD)	18 channels	They Compared the EEG signals before and after OM chanting to observe its effects on the brain.		
[71]	EMD-DWT domain	8 channels	They decomposed each intrinsic modal function signal into subbands by discrete wavelet transform.	This method can effectively analyze non-stationary signals such as electroencephalogram.	This method lacks sufficient research on extracting features other than entropy features.
[72]	AR	6 channels	They took the reflection coefficient of EEG signal as potential feature and use autocorrelation value to extract the reflection coefficient recursively.	Autoregressive modeling can be a significant time saver in extracting some concise features.	AR parameters have poor noise resistance, so it is necessary to explore the feasibility of other features in this extraction method.
[73]	SVD	128 channels	They used driving simulators to assess cognitive distraction.	SVDS can significantly improve the accuracy of EEG data representation of changes related to drivers' cognitive distraction.	The computational complexity is high, especially on dense large-scale matrices.

x(self), hence the name AR model. In AR modeling of EEG, Rahman et al. [72] directly extracted reflex coefficient from a given frame of EEG data by recursion using autocorrelation values as EEG features for classification experiment, which led to improved classification results and better representation of psychological classification.

F. Singular Value Decomposition (SVD)

SVD is an important matrix factorization in linear algebra, and SVD is the generalization of eigendecomposition on arbitrary matrices. It has important applications in signal processing, statistics, and other fields. SVD has advantages in characterizing changes in EEG data related to changes in driver distraction, so the research on driver distraction is very effective and is often used in feature extraction. Almahasneh et al. [73] proposed a new EEG feature extraction method based on SVD, which maximized the accuracy of driver cognitive distraction detection and made the detection results more accurate than before.

VII. Distraction Detection Based on EEG

Classifiers used in EEG analysis and classification algorithms in driver state research can be divided into traditional machine learning classifiers and deep learning-based classifiers. Traditional methods are mainly advanced classifiers based on mathematical models, while deep learning methods are based on different neural network models. A summary of the methods, including both classifiers, is shown in Table V.

Both traditional methods and deep learning methods belong to machine learning methods for classification tasks. Traditional methods are mainly based on mathematical theory classification techniques and simple mathematical models, while deep learning methods are mainly based on neural networks. Due to the relatively simple structure of the traditional method, the time used for classification data is also shorter than that of the deep learning method, and the training process of the traditional method is not easy to be overfitting. However, with the development of neural networks, deep learning methods can greatly improve the accuracy and robustness of classification and obtain better classification results than traditional methods.

A. Traditional Classifier

1) Decision Tree: Decision tree learning is one of the most widely used and practical methods in inductive reasoning. It is a method of approximating discrete-valued functions, which is robust to noisy data and can learn disjunctive expressions. Decision tree learning is a method of approximating a discrete function, and the learned function is represented by a decision tree. The learned tree can also be expressed as an if-then rule set to improve human readability. Polat and Güneş [75] proposed a hybrid system consisting of FFT feature extraction and decision tree classifier decision to detect seizures in EEG signals. Dehzangi and Taherisadr [91] proposed a systematic approach based on EEG to assess driver inattention states. By screening the key features of distraction and using the decision tree classifier to detect driver distraction for all subjects, a high classification accuracy was obtained.

2) Random Forest: In machine learning, random forest algorithm is a method that combines multiple decision trees, following the principles of ensemble learning. The resulting output category is determined by analyzing the category output patterns of a single tree. In the classification task of distraction detection, the process begins with the selection of bootstrap samples from the training dataset, upon which a decision tree is constructed. Then, several variable candidate sets are randomly selected from the whole variable set at

TABLE V
CURRENT MAINSTREAM DISTRACTOR STATE CLASSIFIERS

	Method name	Principle of algorithm	Drawbacks of algorithm	Test environment: Laboratory simulation	Test environment: Real car	Accuracy(%)	Reference
Traditional method	Decision tree	It searches all possible decision tree Spaces without backtracking.	When the type of distraction increases, the classification effect becomes worse.		√	98.99±1.2	[91]
	Random Forest	It finds the root node and randomly splits the features.	When the distractor features increase, the feature weights of the classifier will become untrustworthy.		√	75.91	[76]
	KNN	It assigns a new unclassified example to the class to which most of its k nearest neighbors belong.	When the training samples are not balanced, the distractor detection results will be misleading.	√		71.1	[77]
	SVM	Solving binary nonlinear decision surface with kernel function.	It is difficult for SVM to deal with classification tasks with more than two types of distraction.	√		84.6±5.8	[82]
	Naive Bayes	Bayes' theorem of independent characteristic conditions.	The effect of distraction detection is poor when the correlation of each distraction type is strong.	√		82.6	[83]
	FS Clustering	It finds the center of a particular cluster by removing data points within a fuzzy radius.	The model is computationally intensive and time-consuming.	√		79.21	[84], [85]
Deep learning method	FFNN	The signal propagates one-way from the input layer to the output layer.	It is easy to overfit.		√	80.7	[82]
	CNN	A multi-layer neural network which can freely set the stepping direction of the function as required.	The correct training of the model usually requires a large amount of labeled data.	√		95.76	[83]
	RNN	It deals only with the first few steps that the network needs to remember.	It is prone to gradient explosion and gradient disappearance.	√		88.1	[84]
	FNN	It makes fuzzy decisions through fuzzy controller, and then enters the next loop after output.	Most of them are supervised learning, and it is difficult to achieve adaptive learning.	√			[85]
	PNN	Prediction and classification are made according to the maximum a posteriori probability criterion.	It is easy to lose feature information in the training process.	√		69.72	[81]
	AE	It encodes input data using a deep network and reconstructs input data using a decoder network.	The model generalizes poorly.	√			[90]
	LSTM	It determines the information in each round of the network through additional gates.	The gradient problem still has room for optimization.	√			[87]
	BiLSTM	It processes forward and learns input information backward through two layers of LSTMs.	The model cannot compute in parallel.		√	92.48	[63]
	Transfer Learning	Train only a few layers of the network and freeze the parameters, then apply them to similar data.	The model parameters are not easy to converge under transfer learning method.	√		98.5	[88]
	GRU	Update gates and reset gates are added to each layer of RNN to control the network memory.	Like LSTMS, it suffers from gradient issues and parallel computation issues.	√		92	[16]
	HNN	A new network is formed by integrating the structures of multiple neural networks	The design of specific network structure is difficult.		√	92	[90]

each segmentation, and the above steps are repeated until it is large enough to obtain the minimum classification error. Finally, a trained random forest classifier can classify the test set by voting the results of all the trees. Zuo et al. [76] proposed a driver distraction detection framework based on EEG complexity feature fusion, using random forest for distraction detection, and obtained a certain level of classification accuracy.

3) K-Nearest Neighbor (KNN): KNN means that each sample can be represented by its KNNs. KNN as an effective classification model has been developed relatively mature. After algorithm optimization, KNN has also derived some improved algorithms, such as AKNN, DKNN, KNNDW, and KNNNB. The basic idea of applying KNNs can be understood as: in a feature space, if most of the KNN samples of a sample can be classified into a certain category, then this sample is also divided into the category to which most of the nearest neighbor samples belong. Kumar et al. [77] used different machine learning algorithms to classify cognitive distraction and visual distraction, and the KNN algorithm performed well compared to other machine learning algorithms.

4) Support Vector Machine (SVM): SVM is a machine learning algorithm proposed in the 1990s, primarily utilized in data mining applications. It is a classification algorithm whose idea can be understood as drawing a perfect line. A line that can be exactly in the middle of the two groups to be classified is the same distance from the points of the two groups. As a commonly used classification algorithm, SVM is mostly used to classify linearly separable data and nonlinearly separable data [92]. Distraction detection is a typical binary problem. It is common to detect drivers' EEG characteristics based on SVM. Wang et al. [78] developed a countermeasure to track the driver's attention focus. They used SVM as a classifier for dual-task distraction detection and finally achieved good classification results.

5) Naive Bayes: Naive Bayesian method is a classification method. The theoretical basis of this method is Bayes' theorem and the assumption of independence of characteristic conditions. The naive Bayes model was first proposed in 1960 [93]. By the 1990s, classifiers based on Bayesian networks gradually matured. The idea of naive Bayes classification is to take the independence between feature words as the premise and first learn based on the known dataset to obtain the joint probability distribution from the input to output. Based on this distribution, input the independent variable, and get the dependent variable with the largest posterior probability. Classifiers based on Bayesian networks have many advantages, such as being able to adapt to complex data and classification problem settings, and perform well in solving practical problems. Li et al. [79] extracted the energy features of wavelet packet coefficients as the input of Bayesian theory model for driver behavior and intention recognition, so as to predict whether the driver is in a distracted state. The final classification results are ideal.

6) Fuzzy Subtractive (FS) Clustering: FS clustering is a fast, one-time algorithm used to estimate the number of clusters and cluster centers in a set of data. This technique relies on the measurement of the density of data points in the feature space. The purpose is to find areas with high data point density in the feature space. The point with the largest number of neighbors is considered the center of a particular cluster. Wali et al. [80] used two features to detect the distraction of different wavelets by applying the fuzzy inference system classifier, and got a good classification effect.

B. Deep Learning Classifier

1) Feedforward Neural Network (FFNN): In the research of using EEG to detect driver distraction, FFNN is a very common and effective neural network topology. Its advantage lies in its robustness when faced with different types of input features. However, the FFNN model requires a lot of computing power when estimating weights and deviation factors and has high requirements on hardware.

Moreover, the FFNN model may cause overfitting problems due to improper selection of neurons and layers during the training process. Xing et al. [82] used FFNN to identify the secondary tasks that would cause distraction from different driving tasks, and the average accuracy of the final test results was high.

2) Convolutional Neural Network (CNN): The CNN model topology is a neural network that generally includes a convolutional layer, a fully connected layer, and a pooling layer. According to the task's requirements, the number of convolutional and pooling layers can be increased to obtain more reliable data. In the study of driver distraction, the CNN model can apply end-to-end learning technology, directly taking EEG signals as input, and then outputting the driver's mental state. Almogbel et al. [83] proposed an end-to-end CNN deep neural network learning model in the driver workload study. This model can accommodate the original EEG signal of four channels as input. Also, these signals come from numerous driving sessions within a month.

3) Recurrent Neural Network (RNN): RNN is a type of recurrent neural network that takes sequence data as input, recursively in the evolution direction of the sequence, and all cyclic units are connected in a chain. Its development is based on the idea of parameter sharing [94]. The research of cyclic neural network began in the 1980s and 1990s, and it evolved into a deep learning algorithm in the early 21st century. Two common variations of recurrent neural networks are bidirectional RNN (Bi-RNN) and long short-term memory networks (LSTMs). In a driver's intention detection experiment, Moinnereau et al. [95] applied RNN and finally obtained more accurate results. Kumar et al. [84] used RNN and other models to classify cognitive load tasks, in which cognitive load tasks were divided into external cognitive secondary tasks (distracted tasks) and nontasks. Finally, it is found that the classification result of RNN is superior to other models.

4) Fuzzy Neural Network (FNN): Both neural networks and fuzzy systems belong to pattern recognition algorithms. The FNN model is a neural network that combines an artificial neural network (ANN) with a fuzzy system. FNN amalgamates the strengths of both, eliminating the need for prior knowledge while ensuring a transparent learning process and high efficiency. Liu et al. [85] proposed a generalized prediction system based on recursive self-evolving fuzzy neural networks to detect EEG characteristics of drivers when they are tired. The results show that their proposed FNN network is superior to the competitive model regardless of whether cyclic or acyclic structures are used.

5) Probabilistic Neural Network (PNN): PNN is a neural network commonly used for pattern classification. PNN is a neural network model based on statistical principles. It is equivalent to the optimal Bayes classifier in the classification function. Its essence is a parallel algorithm developed based on the Bayesian minimum risk criterion. At the same time, it is not like traditional multilayer forward networks that need to use the BP algorithm to calculate the backward error propagation, but a completely forward calculation process. Wail et al. [81] also used PNN to classify the level of driver distraction, achieving results slightly below those of subtraction fuzzy clustering, yet demonstrating practicality.

6) Autoencoder (AE): AE is an unsupervised deep learning algorithm, and it is also an important research direction in the future. It can be used to estimate the output in a manner that closely resembles the input data. However, at present, the application of AE classifier in the research of driver distraction based on EEG is relatively limited. Zhang et al. [86] performed an AE model to adapt a specific type of encoder–decoder model to unsupervised learning, followed by distraction detection. They ended up with high detection accuracy.

7) Long Short-Term Memory Network (LSTM): LSTM is a kind of special time cycle neural network, which is specially designed to solve the long-term dependence problem of common RNNs. The LSTM contains blocks, which in some literature may be described as intelligent network units because they can remember values of indefinite lengths of time. The blocks determine whether a previous input is important enough to be remembered and output. Monjezi Kouchak and Gaffar et al. [87] used a stacked LSTM network with attention to detect driver distraction in driving data and obtained more accurate detection results after comparison with normal stacked LSTM and MLP models.

8) Bidirectional Long Short-Term Memory Network (BiLSTM): The difference between BiLSTM and ordinary LSTM is reflected in the LSTM block. Bidirectional LSTM blocks, in which two layers of LSTM storage cells simultaneously process sequences in opposite directions, provide more temporary context over a longer time horizon in many applications. While traditional LSTM block processing relies on the output of the previous unit, the flow of information is one way. Zuo et al. [63] proposed a new framework based on sliding window MSE and BiLSTM to explore EEG distraction information and detect driver distraction in real traffic using multimodal signals. With this framework, they improved the accuracy of distraction detection.

9) Transfer Learning: Transfer learning is a method of machine learning in which a pretrained model is reapplied to another task. In the field of driver distraction detection, there is very limited data available. Although the network model may have high accuracy on a few training samples, the generalization effect is poor. When the existing deep learning model is applied to sample data with similar characteristics, only several layers of the network can be trained and the trained network parameters can be frozen. In this way, the new model trained not only saves a lot of calculation time but also has good generalization accuracy on the test set. Zhang et al. [88] selected ResNet50 and VGG16, two commonly used transfer learning models based on CNNs, to detect drivers' distracted behavior and finally achieved a high detection accuracy.

10) Gated Recurrent Unit: Gated recurrent unit (GRU) and LSTM are both RNN variations, and LSTM inspired the development of GRU. The primary idea of GRU is to add two gates, an update gate and a reset gate, to each layer of RNN to regulate short-term memory and long-term memory. Convolutional approaches and GRUs were utilized by Li et al. [16] to trace the association between driver distracted states and EEG signals in the time domain. They used both temporal and spatial information of EEG signals as model input and compared it with networks that used either temporal or spatial information alone. Simulator studies were used to validate the effectiveness of the proposed strategy.

11) Hybrid Deep Neural Networks: Hybrid deep neural network (HNN) refers to a neural network that is an ensemble of multiple neural networks. Since EEG is a kind of time series data and there are usually multiple EEG electrode channels, HNNs can play a better role than a single neural network. Lee et al. [89] organized ten pilots to conduct experiments in a simulated flight environment, and they proposed an HNN consisting of five convolutional blocks and one LSTM block to classify the degree of distraction. Aljasim and Kashef [90] proposed a new scalable model called E2DR, which combines two or more deep learning models together using a stacked ensemble approach to improve accuracy. This model is adaptable to a variety of networks and has a high degree of generalizability.

VIII. Information Fusion-Based Distraction Detection

A. EEG and Eye Movement

The majority of information perceived by drivers comes from visual channels. Eye movement signals are the primary physiological markers that convey visual distraction. Baumann et al. [96] used occlusion techniques to conduct experiments and finally succeeded in quantifying the degree of distraction with gaze behavior. This proves that eye movement signals can be used to assess a driver's driving state, that is, for distraction detection. Le et al. [97] proposed a model composed of VOR and OKR. Even under real-world situations, this model has a good estimating effect in imitating unconscious eye movements. Their goal in developing this model is to solve the problem of both visual and cognitive distraction recognition, as traditional eye movement detection is unable to deal with the "seeing but not seeing" in the state of cognitive distraction. An increasing number of eye movement data study teams have discovered that typical eye movement features cannot effectively assess whether a person is preoccupied. The researchers are looking for ways to optimize their eye movement recognition technology to accurately identify interference. In addition to Le et al.'s approach of developing better models, the idea of using other physiological signals and eye movement signals to combine detection is also emerging. Therefore, the combination of eye tracking and EEG distraction detection has become a new research field.

The primary problem with combining these two physiological signals is that the eye movements in the EEG record produce artifacts. To address this issue, Plöchl et al. [98] proposed an algorithm that uses eye tracker information to objectively and automatically identify ICA components related to eye artifacts. They combined EEG and eye tracking to detect eye movement artifacts in the EEG and correct the artifact components related to eye movement. Rodrigue et al. [99] proposed a method using EEG and eye tracking to detect distractions during reading. EEG classification is more accurate, while eye tracking data are more effective in certain types of applications. By combining EEG and eye tracking features, they found that the classification results are better than using either mode alone in most cases. Savage et al. [100] evaluated the impact of secondary cognitive task requirements on eye movement and EEG indicators and conducted experiments with eye trackers and EEG. They found that the driver's eye movement data and EEG indicators were very sensitive to changes in cognitive load before the danger occurred. In the end, they found that changes in certain aspects of the saccadic eye movement system can be used as a sign of distraction and that such changes can be detected even before the danger occurs.

B. EEG and Driving Performance

Lane changes, steering control, reaction time to danger, and other aspects of driving performance are all important markers of cognitive and visual distraction. Numerous studies have looked into how secondary tasks affect driving performance [101], [102]. These studies all confirm the scientific nature of driving performance as an indicator of distraction detection. The researchers have developed a model that captures EEG activity, which can better understand the effects of distraction on driver behavior by capturing changes in EEG [103]. It is demonstrated that EEG and driving performance interact in the study of distraction detection, and the combination of the two can improve the performance of distraction detection.

Lin et al. [104] investigated the viability of a monitoring feedback system that uses EEG to track physiological alterations and awaken drowsy drivers while recording observations about the driver's performance behind the wheel. Their study found that the arousal feedback could immediately reverse the deterioration of driving performance after the driver entered a state of cognitive distraction. Meanwhile, the EEG was accompanied by θ and α power inhibition of bilateral occipital EEG. This suggests that EEG can quantify driving performance status and evaluate distraction detection together with driving performance indicators. To assess how sleep-deprived cognitive distraction affects EEG measurements and driving performance in real-world driving conditions, Perrier et al. [105] had subjects that perform a monotonous highway driving task on the road for an hour in normal and sleep-deprived conditions. To ensure safe driving, they simultaneously recorded EEG. Finally, they concluded that drivers' driving performance and EEG frequency band correlations were higher in sleep deprivation than in normal sleep, demonstrating the effectiveness of the combination of driving performance and EEG in detecting distraction. Ban et al. [106] collected data from the subjects and coupled driving behavior analysis with EEG analysis to better understand how seizures impact driving ability. They created a mobile driving simulator that can capture driving-related metrics through video electroencephalogram in real time. They were able to successfully record the case's behavior and changes in EEG, discovering that both reflect the driver's distracted condition. Another driving ability evaluation study can be found in [107].

C. EEG and Images

Images can reflect a person's emotional information, and such images are called emotional images. Emotional images can reflect the driver's various mental states, such as sleepiness, anger, and concentration, which are closely related to whether the driver is distracted. An EEG can reflect a person's mental state or state of distraction, so EEG can be combined with images to better identify a driver's state of distraction.

Thiruchselvam et al. [108] tested the two predictions made by the emotional regulation process model in two phases by measuring the responses of the electrical cortex to neutral and emotional images. In the adjustment phase, they use distraction or reappraisal methods to observe or adjust the image. In the reexposure phase, the same image is passively viewed. They combined EEG and emotional image analysis and finally proved that in the process of emotion generation, distraction and reevaluation are intervened at different stages.

IX. Open Issue and Future Directions

A. EEG Responses to Different Distractions

As mentioned earlier, distraction can be divided into visual, cognitive, auditory, and physical/biomechanical interference. When these kinds of distractions happen, drivers behave differently. Generally speaking, they can be described as the eye trajectory leaving the road, the brain becoming diverted, the ears attending to auditory information other than driving, and the hands leaving the driving area. When distraction occurs, the driver's driving speed, lateral control, and reaction time will almost all be affected [109]. However, the performance of the impact varies. Similarly, returning to the physiological indicator of EEG, when faced with different types of distraction, its signal characteristics will also be different. This has also led to different distraction tasks, such as auditory tasks, visual tasks, and math tasks, researchers will use different signal processing methods. Therefore, the main question is how to find a way to effectively process the EEG signals from different types of distractions. One way to solve this problem in the future is to develop a method that combines physical measurement and biological measurement. Physical measurement is more aimed at measuring auditory distraction, visual distraction, and so on, while biometrics is aimed at cognitive distraction.

B. Portable EEG Acquisition Equipment in a Real Driving Environment

Currently, many experiments to detect driver distraction have been conducted in the laboratory, while few experiments have been conducted in the real driving environment, and it is difficult to improve the accuracy. Because the commonly used head-mounted EEG measuring device is not well suited to natural driving conditions, it is not easy to carry. Moreover, when the driver is engaged in various tasks, the signal fluctuation is larger than that in the laboratory environment, and the signal collected in the real environment is also affected by the noise. These can lead to uncontrolled interference with data acquisition. In addition, in the laboratory environment, some subjects believed that driving errors would not cause serious harm, which also led to a decrease in the reference significance of EEG signals collected. In view of the above problems, it is necessary to make the equipment based on EEG collection portable and apply it to the actual driving environment. Several research teams have been working on this in recent years. Hu et al. [110] designed a novel wearable EEG data acquisition sensor. They devised a sensor that uses fewer electrodes, leads connected at several points, and solid gel pads to achieve the goal of being lightweight. The final results demonstrate that the device's signal effect is satisfactory.

C. Lightweight Information Fusion Method

Multimodal information fusion has always been one of the future development directions of distraction detection. Simultaneously, the effect of employing EEG, eye movement, ECG, myoelectric signal, and other physiological signals for distraction detection is potentially superior to using just one or two physiological signals. Because the effect of information fusion detection is to make the overall detection performance more reliable. When the detection device detects numerous signal sources at the same time, the likelihood that when the detection result of one signal is incorrect, the results of other types of signals are also incorrect is considerably reduced [110]. In other words, additional detection signals can compensate for a particular detection signal's mistake. However, multimodal information fusion technology has some problems. The increased number of sensors increases the system's complexity [111]. In addition, the complexity of the detection system will also increase as it moves toward civilian use. With an increase in users, the system will encounter a condition never seen before in the laboratory stage, bringing a wealth of new information to the detection system. Therefore, it is necessary to lightweight the multimodal information fusion detection technology in terms of both software and hardware: software to reduce the complexity of the detection system and hardware to simplify the number of sensors and lines. At present, the method of lightweight fusion model in the front end is mainly based on deep learning. Related research teams have proposed fusion models based on DNN, LSTM, hybrid network, and fuzzy transformation methods, all of which have shown good results in lightweight fusion information features.

D. Real-Time Distraction Detection

High-precision and real-time condition detection is a necessary condition for dealing with actual driving environment. Driver assistance systems with distracted driving detection functions can help to reduce the occurrence of distraction, but different drivers have different physical characteristics, habits, and behaviors [112], and organizing subjects to conduct experiments cannot always cover all real-world scenarios. As a result, developing real-time state detection algorithms that can be employed by diverse drivers is a critical step in moving distraction detection from the laboratory to the real driving environment. The aim of developing driver assistance systems for real-time monitoring is to reduce the risk of accidents by issuing alerts in advance and constantly checking drivers' driving behaviors [112], [113]. Real-time driving applications, including real-time distraction detection, have received increasing attention in recent years. The current cutting-edge approaches mainly focus on developing real-time distraction detection systems based on cameras by using lightweight deep learning technologies. However, images collected by cameras may be easily affected by illumination (e.g., nighttime driving), weather (e.g., rain and snow), or occlusion of the target object (e.g., driver face occluded by hands or arms). The fusion of information from different sensors can be a promising solution to overcome the limitations of a single sensor type [113]. As a result, future techniques would concentrate on the integration of cameras and wearable physiological sensors for real-time applications on embedded systems.

E. Acquisition Device Optimization

When a subject wears EEG devices for experiments, the weight, structure, and fitness of the device will have an influence on the subject. This influence may cause subjects to be distracted during the experiment, and this distraction is obviously not consistent with the type of distraction corresponding to the designed distraction task, thus affecting the experimental results. Therefore, this distraction, caused by the experimental equipment, needs to be avoided in the experiment by optimizing the experimental equipment. EEG acquisition equipment needs to be optimized from two perspectives: hardware structure optimization and data processing optimization, in order to enable normal implementation of distraction detection while minimizing the influence of acquisition equipment on subjects. Li et al. [115] used an ARM microcontroller processor and an ADS1299 chip to design an EEG acquisition device that was imperceptible to the subject. They optimized the hardware of the acquisition device by using small hardware and soft electrodes. Simultaneously, pure EEG signals were extracted using time-domain, time–frequency domain, and nonlinear features, and the multiscale entropy MSE and sleep EEG datasets were extended using Sleep-EDF before feature extraction. Finally, they confirmed that the device was capable of collecting the needed EEG data. Similar technologies should be developed in the future to improve the EEG data capture device by decreasing data collection sounds.

F. Multimodal Fusion Distraction Detection

Driver distraction detection based on multimodal (EEG, eye movement, electromyography, and computer vision) data is one of the future directions for distraction detection. The main challenges include multimodal data acquisition, multimodal data processing, and multimodal data classification [115]. In terms of multimodal data acquisition, the current mainstream equipment is the laboratory simulation driver platform integrating multiple sensors. The sensors, including eye trackers, biosensors, and image collectors, are integrated into a comprehensive driving platform for multimodal data collection. However, these laboratory platforms are usually difficult to be deployed in real vehicles because of the complex and expensive sensors. Improving these sensors (particularly biosensors) to make them easily worn for accurate data gathering should be a top priority for future practical applications. In the aspect of multimodal data processing, the current approaches extensively focus on feature fusion of the multimodal data. The fusion algorithms are mainly divided into traditional fusion and deep fusion. With the advancement of deep learning technologies, future efforts should be more focused on the development of deep fusion methods for robust detection. In terms of multimodal data classification, the current studies mainly focus on designing a single classifier based on fused features or simply stacking various classifiers, which may not well mine the potentials of multimodal data because the characteristics of different signals should be treated differently to optimize their potentials for better detection performance. Future research can construct different classifiers for different signals and develop fusion algorithms to weight the findings from different classifiers thoroughly for improvement.

X. Conclusion

This study provides a thorough summary of the research on EEG-based driver distraction detection and its projected development trends. The overall research can be divided into several parts: the study of driver distraction, the processing of EEG signals, the relationship between EEG and distraction, the feature extraction and classifier involved in EEG-based distraction detection, and the research of the fusion of EEG and other physiological signals. In Sections II and III, a detailed analysis of driver distraction research is presented in conjunction with publicly available distraction datasets. The link between EEG and distraction is reviewed in Sections IV and V in terms of EEG collection, preprocessing, band characteristics, and changes in EEG performance in different distractor conditions. Section VI then outlines the EEG feature extraction methods used in distraction identification, while Section VII gives a detailed study of traditional and deep learning-based classifier algorithms used in EEG distraction detection. Due to issues such as low EEG signal strength, complex acquisition equipment, and a lack of natural-environment experiments, research on multimodal physiological signal fusion distraction detection, lightweight hardware, and portable experimental equipment will become new challenges in the future, especially for driver assistance in mixed traffic flow scenarios or cooperative driving and decision-making in intelligent transportation systems [119], [120].

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