IRAQI Academic Scientific Journals

Tikrit Journal for Computer Science and Mathematics

available online http://tjcsm.tu.edu.iq/

An EEG based Physiological Signal for Driver Behavior Monitoring Systems: A Review

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Keywords:

EEG, Driver Behavior, drowsiness, Mental Workload, Fatigue, Attention and Distraction.

ARTICLE INFO

Article history:

Received	30 Sep. 2023
Accepted	15 oct. 2023
Available online	30 Dec. 2023

Citation: Z.T. Al-Qaysi, An EEG based Physiological Signal for Driver Behavior Monitoring Systems: A Review.

Tikrit Journal for Computer Science and Mathematics 2023; 1(1): 38-54

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Publisher: Tikrit University

Abstract:

Driving is a process that requires multiple skills, such as handling motor and visual capabilities, along with more alertness, mental planning, and memory resources. Human beings can interpret these cognitive skills and predict psychological behavior continuously. Driving behavior recognition is the foundation of driver assistance systems, with potential applications in automated driving systems. Most prevailing studies have used subjective questionnaire data and objective driving data to classify driving behaviors, while few studies have used physiological signals such as electroencephalography (EEG) to gather data. Therefore, this research aims to study the driver behavior monitoring systems based on the electroencephalography (EEG) technique to study the neuronal changes occurring while driving. Fundamentally, four significant databases, namely IEEE, ScienceDirect, Web of Science, and PubMed were considered to contain a considerable number of technical and scientific articles relevant to the topic of this study from 2010 to 2022. The final set of papers that have been identified was 70 articles. It can be deduced that it is hard to depict the implications of EEG-based driver behavior monitoring systems. Therefore, this study gave a clear picture and better understanding of how to cope with all the technical and scientific issues in the academic literature for this integrated framework. Additionally, this research provides state-of-the-art data acquisition and recording techniques for EEG data processing in EEG-based driver monitoring systems.

إشارة فسيولوجية تعتمد على تخطيط كهربية الدماغ (EEG) لأنظمة مراقبة سلوك السائق: مراجعة

الخلاصة

القيادة هي عملية تتطلب مهارات متعددة، مثل التعامل مع القدرات

الحركية والبصرية، إلى جانب المزيد من اليقظة والتخطيط العقلي وموارد الذاكرة. ويستطيع الإنسان تفسير هذه المهارات المعرفية والتنبؤ بالسلوك النفسي بشكل مستمر. يعد التعرف على سلوك القيادة أساس أنظمة مساعدة السائق، مع تطبيقات محتملة في أنظمة القيادة الآلية. استخدمت معظم الدراسات السائدة بيانات الاستبيان الشخصية وبيانات القيادة الموضوعية لتصنيف سلوكيات القيادة، في حين استخدمت دراسات قليلة الإشارات الفسيولوجية مثل تخطيط كهربية الدماغ (EEG) لجمع البيانات. لذلك يهدف هذا البحث إلى دراسة أنظمة مراقبة سلوك السائق بالاعتماد على تقنية تخطيط كهربية الدماغ (EEG) لدراسة التغيرات العصبية التي تحدث أثناء القيادة. بشكل أساسي، تم اعتبار أربع قواعد بيانات مهمة، وهي IEEE و ScienceDirect و Web of Science و PubMed، التي تحتوي على عدد كبير من المقالات التقنية والعلمية ذات الصلة بموضوع هذه الدراسة من عام 2010 إلى عام 2022، حيث ان المجموعة النهائية من الأوراق التي تم تحديدها كان 70 مقالة. يمكن استنتاج أنه من الصعب تصوير الآثار المترتبة على أنظمة مراقبة سلوك السائق المستندة إلى مخطط كهربية الدماغ(EEG). لذلك، أعطت هذه الدراسة صورة واضحة وفهماً أفضل لكيفية التعامل مع جميع القضايا التقنية والعلمية في الأدبيات الأكاديمية لهذا الإطار المتكامل. بالإضافة إلى ذلك، يوفر هذا البحث أحدث تقنيات الحصول على البيانات وتسجيلها لمعالجة بيانات تخطيط كهربية الدماغ في أنظمة مراقبة السائق القائمة على تخطيط كهربية الدماغ.

1. INTRODUCTION

Driving is one of the most common attention-demanding tasks in daily life [1]. They require multiple skills such as handling motor and visual capabilities along with more alertness, mental planning, and memory resources. Human beings are inherently to interpret these cognitive skills continuously and to predict psychological behavior along with sources of distraction [2]. As a consequence, people are more susceptible to fatigue, drowsiness, cognitive deficits, or a combination of these, imposing a significant impact on their health, functioning, and safety. In particular, driving performance can be profoundly impaired under the influence of fatigue and drowsiness , increasing the risk of motor vehicle collisions [3]. A lot of research has been conducted to measure and quantify a driver's condition, including workload, stress, fatigue and drowsiness, based on physiological signals obtained from the driver. Physiological data such as EEG, Electrocardiogram (ECG) and Electromyogram (EMG) have been used separately or in combination [4, 5]. Previous studies have found that EEG signals can accurately reflect the physiological state of human beings, and are recognized as the "golden standard" to evaluate vigilance, which has been widely used in vigilance detection [6-8]. This study tried to give researchers a deep insight into the current trends in the field of Brain Computer interface and artificial intelligence and their applications in the driver behavior monitoring applications. This study designed to cover the most important research perspective in the phenomenon of the selected research topic. As a result, a brief discussion for the available methods and techniques that have been used in the state of art was discussed. These methods and techniques cover three main perspectives in driver monitoring systems, which is namely, the data acquisition and the recording, the pattern recognition, and the driving environment. Additionally, the motivation of driver behavior monitoring using EEG, monitoring the emotional state, monitoring mental workload, and monitoring the fatigue state and drowsiness. Furthermore, the existing challenges in literature was highlighted, and recommended solutions to solve these challenges.

2. METHOD

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses were used to perform this investigation [5, 9, 10]. The researchers should avoid depending on a single database to look for literature in the overview article; no single database is likely to include all relevant references; hence, a supplemental search is almost always necessary [11]. According to the studies [12-14], a thorough overview should be done across several databases to capture most publications.

3. RESULT AND DISCUSSION

This review delves into the results and discussions surrounding using EEG-based physiological signals in driver behavior analysis by exploring the outcomes of various studies and synthesizing key findings via fatigue, workload, drowsiness, attention, distraction, and driving style.

3.1. Fatigue

Here [15], they assessed the validity of a single-channel EEG device (TGAM-based chip) to monitor changes in mental state (from alertness to fatigue). They collected subjective ratings of alertness and fatigue, as well as driving performance. they found that the power spectra of the delta EEG band showed an inverted U-shaped quadratic trend (EEG power spectra increased for the first hour and half, and decreased during the last thirty minutes), while the power spectra of the beta band linearly increased as the driving session progressed. Coherently, saccadic velocity linearly decreased and speeding time increased, suggesting a clear effect of fatigue. In this study [16], they measured mental fatigue in drivers using electroencephalogram (EEG) and electrocardiograph (ECG). Together, thirteen healthy subjects performed a continuous simulated driving task for 90 min with simultaneous ECG and multi-channel EEG recording of each subject. The results show that the EEG alpha and beta, the relative power, the amplitude of P300 wave of event-related potential (ERP), the approximated entropy of the ECG, and the lower and upper bands of power of heart rate variability (HRV) are significantly different before and after finishing the driving task ($p < 0.05$). These metrics are possible indices for measuring simulated driving mental fatigue. In this work, they designed a fatigue driving simulation experiment and collected the electroencephalogram (EEG) signals. Complex network theory was introduced to study the evolution of brain dynamics under different rhythms of EEG signals during several periods of the simulated driving. The results show that as the fatigue degree deepened, the functional connectivity and the clustering coefficients increased while the average shortest path length decreased for the delta rhythm. In addition, there was a significant increase of the degree centrality in partial channels on the right side of the brain for the delta rhythm. Therefore, it can be concluded that driving fatigue can cause brain complex network characteristics to change significantly for certain brain regions and certain rhythms[17]. In this paper, they report a novel hybrid vigilance monitoring and warning system based on EEG and eye movement signals to detect mental drowsiness. This system collects eye movement information to quickly detect unsafe driving behavior and also gives real-time warning of driving fatigue by monitoring EEG activity. It also uses Fisher score electrode analysis to locate the cortical regions involved in vigilance and reduces the number of channels required. The self-adaptive system can provide various online monitoring and warning strategies for adapting to different individual physiological situations and complex external environments[18]. In this paper, they used Bayesian Network (BNs) to develop a detection model of driver emotion with electroencephalogram (EEG), which considers two factors of driver personality and traffic situation. The preliminary experiment results suggest that this method is feasible and therefore can be used to provide adaptive aiding[19]. This research presents approaches for alertness detection based on the electroencephalography and power spectrum to evaluate driver's vigilance level in a static driving simulator. Twenty datasets were acquired using the eight-channel wireless headset for EEG signals recording. Two driving tasks, that are Alert Driving (AD) and Fatigue Driving (FD), were instigated for data acquisition, to discriminate the driver's alertness level .To estimate the alertness level, four different frequency-domain power spectral density (PSD) feature extraction techniques were evaluated (specifically periodogram, Lomb-Scargle, multitaper, and Welch). Multilayer Neural Network (MLNN) is used to evaluate the performance of all the extracted features. The highest average accuracy is obtained from PSD using Welch with 96.7% and 85.0% for training accuracy and testing accuracy respectively[20]. In this paper [21]., an expert automatic method based on brain region connectivity for detecting fatigue is proposed. The new feature of Gaussian Copula Mutual Information (GCMI) based on wavelet coefficients is calculated to detect brain region connectivity. Classification for each subject is then done through selected optimal features using the support vector machine (SVM) with linear kernel. Results: The designed technique can classify trials with 98.1% accuracy. The most significant contributions to the selected features are the wavelet coefficients details 1_2 (corresponding to the Beta and Gamma frequency bands) in the central and temporal regions. In this paper, a new algorithm for channel selection is introduced that has been able to achieve 97.2% efficiency by selecting eight channels from 30 recorded channels. This paper [22]aimed to give psychological insight of the existing non-invasive measures for driver and pilot fatigue by differentiating sleepiness and mental fatigue. First, the nature of fatigue for drivers/pilots is elucidated regarding fatigue types and fatigue responses, which reshapes our understanding of the fatigue issue in the transport industry. Secondly, the widely used objective neurophysiological methods, including electroencephalography (EEG), electrooculography (EOG), and electrocardiography (ECG), physical movement-based methods, vehicle-based methods, fitness-for-duty test as well as subjective methods (self-rating scales) are introduced. On the one hand, considering the difference between mental fatigue and sleepiness effects, the links between the objective and subjective indicators and fatigue are thoroughly investigated and reviewed. On the other hand, to better determine fatigue occurrence, a new combination of measures is recommended, as a single measure is not sufficient to yield a convincing benchmark of fatigue. In this study [23], they selected the most important physiological features to predict driver fatigue proactively. Finally, using these critical physiological features, we built prediction models that were able to predict the fatigue transition at least 13.8 s ahead of time using a technique called nonlinear autoregressive exogenous network. The accuracy of fatigue transition prediction was promising for highly automated driving (F 1 measure = 97.4% and 99.1% for two types of models), which demon- strated the potential of the proposed method. In this paper[24], they proposed a novel approach based on clustering on brain networks (CBNs) to alleviate the problem to improve the performance of driver fatigue detection. The clustering algorithm was employed to extract the spatial nodes with distinct connectivity attributes throughout the EEG-based brain networks. the experimental results demonstrated the temporal features from the extracted nodes reduced signal mixing and showed clearer deviations. The detected fatigue based on the imaging method was to an extent consistent with self-reported subjective feelings and most of the critical fatigue was detected before the subjective feelings of fatigue. For all the subjects, 21 of 29 accidents happened after detected fatigue in the simulated driving task. Therefore, the proposed method owns potential value for early warning and avoidance of traffic accidents caused by driver fatigue. This paper [25] explored the EEG signal to detect the driving fatigue. They design a portable EEG acquisition system, which detects the drivers' EEG signals and handles the interference by the median filter, band stop filter and Hilbert-Huang transform. The eigenvalues are extracted by percentage power spectral density. Two methods are proposed to determine the fatigue levels. Experiment results show that the method based on eigenvalue ratio in eyes-open state has 79% accuracy, the method based on BP neural network in fatigue classification has 83% accuracy, and the eyes-close state recognition rate is more than 97%.This study [26] investigated and utilized several common entropies to enhance the characteristic quality of EEG signal, and yielded a better expected outcome than those of several classical algorithms due to the hybrid model. The experimental results using prefrontal EEG for assessing driver fatigue showed that the proposed method is convenient and effective, as validated by 32 healthy participants through double-layer nested cross validation. In addition, multi-entropy measures were evaluated for single-channel EEG fatigue detection, and the results showed that wavelet log-energy entropy (WLE) outperformed the other entropy indices with a better recognition rate and higher computational efficiency. This work[27] solves these problems by using two different approaches. Deep networks are efficient feature generators and extract features in low, medium, and high levels. These features can be generated by using multileveled or multilayered feature extraction. Therefore, we proposed a multileveled feature generator that uses a one-dimensional binary pattern (BP) and statistical features together, and levels are created using a one-dimensional discrete wavelet transform (1D-DWT). A five-level fused feature extractor is presented by using BP, statistical features of 1D-DWT together. Moreover, a 2-layered feature selection method is proposed using ReliefF and iterative neighborhood component analysis (RFINCA) to solve the feature selection problem.

3.2. Workload

In this paper[28], they measured and analyzed the driver's EEG for lane change behavior to measure and quantify drivers' workload. The experiment took place in the real road. they extracted the reference and the lane change behavior section and calculated the EEG variation rates from the EEG values. We performed paired-sample T-test to know EEG variation rate of reference and lane change section. Also, we performed ANOVA analysis to know the difference of EEG variation rate dependent on driving road type. We performed independent samples T-test to know the difference of EEG variation rate dependent on gender types. In this paper[29], they analyzed electroencephalogram (EEG) data collected through an urban road driving test. they extracted five kinds of behavior sections from the data: left-turn section, right-turn section, rapid-acceleration section, rapid-deceleration section, and lane-change section. they selected a reference section for each of these behavior sections and compared EEG values from the behavior sections with those from the reference sections to calculate the EEG variation rates, after which we made the statistical analysis. The analysis results of this study are being used to explain the cognitive characteristics of a driving workload caused by drivers' behavior in the vehicle information system, which will provide information for safe driving by taking into account the driving workload. In this paper[30], they develop a model to predict the driver's EEG level utilizing basic information obtained while the vehicle is being driven. We divided the EEG values into two classes, "normal" and "overload", and extracted useful features from the vehicle driving information, such as engine RPM, vehicle speed, lane changes, and turns. A classification model using a support vector machine was built to predict normal and overload states during actual driving. We evaluated the performance of the proposed method using field-of-test data collected when driving on actual roads, and suggest directions for future research based on an analysis of the experimental results. The aim of this study[31] is to investigate the cognitive workload characteristics which can be applied to the human factors that are applied to the switching of operation control in autonomous vehicles. For this purpose, we analyze test driver's EEG and driving data measured while driving on real roads to find out the difference of the cognitive workload state according to driving behaviors in the Urban Road. We found that female drivers are more likely to be overloaded than male drivers and middle-aged drivers are likely to have more overloaded than young drivers when they did in complex driving. These cognitive workload characteristics can be reflected in the function of switching the operation control right in the autonomous driving system. This study[32] presents the driving mental workload and performance model of ageing drivers in the context of real-time road driving. Twenty paid participants (ten males) with a mean age of 57.8 years old (SD = 2.7) and mean driving experience of 29.6 years (SD = 8.5) took part in driving experiments with three complexity levels of situation: simple situation (SS), moderately complex situation (MCS), and very complex situation (VCS). The driving experiments reveal the following: (1) The subjective workload ratings on mean physical demand score were the highest. (2) The electroencephalogram results show that situation complexity had significant effects on theta relative power and alpha relative power of two channel locations (3) The highest mean NTVs was in VCS. (4) The mean speed variability in the MCS was significantly lower than that of in the SS and VCS. (5) The maximum reaction time was recorded in VCS while the minimum reaction time was recorded in the MCS. The main aim of this study [33] was to analyze the effect of the directional road sign displayed on multi and single-board signs on driver mental workload and behavior. 32 participants including 16 females (mean age=24.7 years, standard deviation=1.9 years) participated in the experiment and completed 3 driving simulation scenes. There are two major findings of the study. First, when the number of place names is less than or equal to 7, the multi-board sign generates more mental workload than the single-board sign does. The alpha band power of the driver's frontal area under the multiple boards is lower and affects driving performance (the deceleration is greater). Second, when the number of place names is more than 7, there is no significant difference in the effect on mental workload whether multi or single-board sign is used. However, compared to the single-board sign, drivers in the case of multi-board sign are likely to reduce the fixation duration and increase the number of saccades. The results suggest that it is not necessary to use multi-board signs when the number of place names is less than 7. In this study[34], in addition to comparing brain function and behavioral function in dual task conditions in three conversations types, the persistent effects of these types of conversations have also been traced. The results show that the content of the mobile phone conversation while driving is the cause of the persistent changes in behavioral and brain functions. Increased time headway and lane departure was observed during and up to 5 min after the emotional conversation was finished. EEG bands also varied in different types of conversations. Cognitive conversations caused an increase in the activity of the alpha and beta bands while emotional conversations enhanced the rate of gamma and beta bands. A meaningful correlation was found between changes in the theta and alpha bands and changes in behavioral performance both during the dual task condition and after the conversation was finished, was also observed.

3.3. Drowsiness

In this study[6], we designed a driving fatigue experiment and a multi-class classifier based on support vector machine (SVM). Firstly, the EEG signals of different vigilance levels are decomposed and reconstructed at seven levels using the Daubechies 4 wavelet (db4) transform method. Feature vectors are input into the multi-class SVM classifier to classify different vigilance levels. we can also get relatively ideal classification accuracy 99.41%. Therefore, the proposed classifier can accurately identify four classes of vigilance levels, reduce the computational complexity, and make the detection system more efficient and practical. This paper [35] presents efficient EEG system for drowsiness detection. By combining the reduction in the number of features with the use of only one differential EEG channel, we have succeeded in developing a more suitable system with good accuracy. In order to verify the performance of our approach, the proposed EEG-based signal processing technique was simulated and tested under Matlab using an existing offline database (MIT-BIH Polysomnographic Database Physiobank); consequently, it provides better drowsiness detection performance than similar published works with an average accuracy of approximately 88.80%. Furthermore, we have implemented our proposed architecture in an ARM based processor platform to complete our virtual prototyping and to get a real evaluation of our drowsiness system architecture. Such system is able to process an epoch of 30 s within 0.2 s. The proposed approach should be easily and efficiently handled by a driver to be warned against any risk from potential drowsiness in real-time. This paper [36]presents the use of eye tracking data as a non-intrusive measure of driver behavior for detection of drowsiness. Eye tracking data were acquired from 53 subjects in a simulated driving experiment, whereas the simultaneously recorded multichannel electroencephalogram (EEG) signals were used as the baseline. A random forest (RF) and a non-linear support vector machine (SVM) were employed for binary classification of the state of vigilance. Different lengths of eye tracking epoch were selected for feature extraction, and the performance of each classifier was investigated for every epoch length. Results revealed a high accuracy for the RF classifier in the range of 88.37% to 91.18% across all epoch lengths, outperforming the SVM with 77.12% to 82.62% accuracy. This research would ultimately lead to development of technologies for real-time assessment of the state of vigilance, providing early warning of fatigue and drowsiness in drivers. This study [1] presented the Uncorrelated Fuzzy Locality Preserving Analysis (UFLPA) for considering the fuzzy nature of the input measurements while preserving the local discriminant and manifold structures of the data. Additionally, UFLPA also utilizes Singular Value Decomposition (SVD) to avoid the singularity problem and produce a set of uncorrelated features. Experiments were performed on datasets collected from thirty-one subjects participating in a simulation driving test with practical results indicating the significance of the results achieved by UFLPA of 94%-95% accuracy on average across all subjects. The present study [37] mainly aimed to assess whether and how sleepiness due to sleep deprivation interacts with Time on Task (ToT) effects both on electroencephalography (EEG) measures and driving performance in real driving conditions. Healthy participants performed a one hour on-the-road monotonous highway driving task while EEG was recorded continuously after one night of normal sleep and after one night of total sleep deprivation. The main outcome parameter in the highway driving test was the Standard Deviation of Lateral Position (SDLP). SDLP and EEG indices (i.e alpha and theta power spectra) increased after sleep deprivation and varied with ToT. The latter was more pronounced after sleep deprivation. Beta power spectra did not differ between conditions but increased with ToT. Changes in SDLP and EEG did not correlate significantly. We conclude that driving performance as well as fatigue and sleepiness fluctuations with ToT were more evident after sleep deprivation as compared to normal sleep. The aim of this research [38] is to develop an automatic method to detect the drowsiness stage in EEG records using time, spectral and wavelet analysis. After a selection process based on lambda of Wilks criterion, 7 parameters were chosen to feed a Neural Network classifier. Eighteen EEG records were analyzed. The method gets 87.4% and 83.6% of alertness and drowsiness correct detections rates, respectively. The results obtained indicate that the parameters can differentiate both stages. The features are easy to calculate and can be obtained in real time. Those variables could be used in an automatic drowsiness detection system in vehicles, thereby decreasing the rate of accidents caused by sleepiness of the driver. This paper[39] proposes a comprehensive approach to explore whether functional brain network (FBN) changes from the alert state to the drowsy state and to find out ideal neurophysiology indicators able to detect driver drowsiness in terms of FBN. Collected EEG signals are then decomposed into multiple frequency bands by wavelet packet transform (WPT). Statistical analysis of network features indicates that the difference between alert state and drowsy state are significant and further confirmed that brain network configuration should be related to drowsiness. For classification, these brain network features are selected and then fed into four classifiers considered namely Support Vector Machines (SVM), K Nearest Neighbors classifier (KNN), Logistic Regression (LR) and Decision Trees (DT). It is found that combining MST method and SL method is actually increasing the classification accuracy with all classifiers considered in this work especially the KNN classifier from 95.4% to 98.6%. Moreover, KNN classifier also gives the highest precision of 98.3%, sensitivity of 98.8% and specificity of 98.9%. Thus, this kind of methodology might be a useful tool for further understanding the neurophysiology mechanisms of driver drowsiness, and as a reference work for future studies or future systems. This paper [2]presents an analysis of Conscious Alert System (CAS) to find out classification in alert or non-alert system using Electroencephalogram (EEG) data. Monitoring and analyzing driver behavior are needed for safe driving. In this work, we aim to develop a system that can detect alert system based on the False Negative and False Positive using

LabVIEW. This study [40] proposed a perceptual function integration system which used spectral features from multiple independent brain sources for application to recognize the driver's vigilance state. The analysis of brain spectral dynamics demonstrated physiological evidenced that the activities of the multiple cortical sources were highly related to the changes of the vigilance state. The system performances showed a robust and improved accuracy as much as 88% higher than any of results performed by a single-source approach. This study [41] proposes applying hierarchical clustering to assess the inter- and intra-subject variability within a large-scale dataset of EEG collected in a simulated driving task, and validates the feasibility of transferring EEG-based drowsiness-detection models across subjects. A subject-transfer framework is thus developed for detecting drowsiness based on a largescale model pool from other subjects and a small amount of alert baseline calibration data from a new user. Compared with the conventional within-subject approach, the proposed framework remarkably reduced the required calibration time for a new user by 90% (18.00 min–1.72 _ 0.36 min) without compromising performance (p ¼ 0.0910) when sufficient existing data are available. These findings suggest a practical pathway toward plug-and-play drowsiness detection and can ignite numerous real-world BCI applications. The aim of the study [42] was to identify potential physiological measures as a basis for the development of systems that are able to detect sleep in drivers during automated driving. A within-subjects study with N = 21 subjects was conducted in a high-fidelity driving simulator. Electromyography, electrodermal activity (EDA), respiration and electrocardiography (ECG) were measured in drivers during states of wakefulness and sleep. Sleep stages were assigned with the electroencephalography as a ground truth. The results indicate the potential of EDA and ECG parameters to differentiate between sleep and wakefulness. Implications for the implementation in DMS are discussed. This study[43] examines the utility of drowsiness detection based on singular and a hybrid approach. This approach considered a range of metrics from three physiological signals – electroencephalography (EEG), electrooculography (EOG), and electrocardiography (ECG) – and used subjective sleepiness indices (assessed via the Karolinska Sleepiness Scale) as ground truth. The methodology consisted of signal recording with a psychomotor vigilance test (PVT), pre-processing, extracting, and determining the important features from the physiological signals for drowsiness detection. Finally, four supervised machine learning models were developed based on the subjective sleepiness responses using the extracted physiological features to detect drowsiness levels. The results illustrate that the singular physiological measures show a specific performance metric pattern, with higher sensitivity and lower specificity or vice versa.

3.4. Attention

The aim of this study[44] was to investigate the impact of anger on attentional processing and its consequences on driving performance. Results indicated that anger impacted driving performance and attention, provoking an increase in lateral variations while reducing the amplitude of the visual N1 peak. The observed effects were discussed as a result of high arousal and mind-wandering associated with anger. In this study[45] they compared electrophysiological signals from drivers and passengers that were riding a vehicle in real road environments. Results indicated the following differences: (1) The number of small saccadic eye-movements was greater in drivers than in passengers, whereas the number of large saccadic eye movements was greater in passengers than in drivers, indicating that passengers tended to look at information irrelevant to safe driving. (2) The amplitude of the P1 component of eye-fixation-related brain potentials time-locked to the offset of large saccadic eye movements was greater in drivers than in passengers, indicating that visual information processing load was lower in passengers. (3) The duration of eye-blinks was longer in passengers than in drivers, indicating that the arousal level of passengers was relatively low. These findings suggest that these electrophysiological indices can be useful measures for evaluating the attention of drivers while riding in Level 3 autonomous vehicles. Possible differences in the attentional state between drivers and passengers are discussed. This paper [46] describe driver behavior and brain dynamics acquired from a 90-minute sustained-attention task in an immersive driving simulator. The data included 62 sessions of 32-channel electroencephalography (EEG) data for 27 subjects driving on a four-lane highway who were instructed to keep the car cruising in the center of the lane. Lane-departure events were randomly induced to cause the car to drift from the original cruising lane towards the left or right lane. A complete trial included events with deviation onset, response onset, and response offset. The next trial, in which the subject was instructed to drive back to the original cruising lane, began 5–10 seconds after finishing the previous trial. We believe that this dataset will lead to the development of novel neural processing methodology that can be used to index brain cortical dynamics and detect driving fatigue and drowsiness. This publicly available dataset will be beneficial to the neuroscience and brain-computer interface communities. This work [47] presents a machine learning-based approach to identify driving-induced stress patterns. For this, electroencephalograph (EEG) signals are utilized as the physiological signals. Three classifiers are utilized in this work, namely: Support Vector Machine (SVM), Neural Network (NN), and Random Forest (RF) to classify EEG patterns on the basis of the subject's self-reported emotional states while driving in various situations. A framework is proposed to recognize emotions based on EEG patterns by systematically identifying emotion-specific features from the raw EEG signal and investigating the classifiers' effectiveness. A comprehensive analysis of various performance measures concludes that among the three classifiers employed in this study, SVM performs better to distinguish between rest and stress state. The evaluation obtained an average classification accuracy of 97.95% ± 2.65%, precision of 89.23%, sensitivity of 88.83%, and specificity of 94.92%. The proposed system[48] based on the electroencephalography (EEG) and blood volume pulse (BVP) signals of drivers were collected in the normal and angry states from the field experiments. Statistical analysis shows that the sample entropy of EEG and BVP signals was viable to be used as the index for identifying angry driving. Based on the obtained EEG and BVP sample entropy, a receiver operating characteristic (ROC) curve analysis was introduced to determine the discriminating threshold of driving anger. The results indicate that, when the EEG sample entropy is between (0.2717, 0.6867) and the BVP sample entropy is between (0.4816, 0.7056), the driver is in the transitional period, which means that the driver can become angry easily when facing the stimulating events. When the EEG sample entropy is smaller than 0.5817 and the BVP sample entropy is bigger than 0.6037, the driver is likely to be in an angry state, with an average accuracy of 80.41%. Therefore, it appears reasonable to use the EEG sample entropy of 0.5817 and the BVP sample entropy of 0.6037as the threshold for identify driving anger. The proposed system [49] acquires brain electroencephalography (EEG) signals of the driver, identifies the underlying emotion using machine learning techniques, and feeds that emotion into the car system where different car components can react to that input. Our results demonstrate the ability of the system to recognize two emotions, namely sadness versus happiness, from the recorded EEG with a mean accuracy of 89.7% across three examined subjects using subject-dependent data. Moreover, when training the system using data recorded from multiple subjects, a mean accuracy of 91.7% is achieved. Taken together, these results indicate the ability of the proposed approach to discriminate between sadness and happiness whose extreme expression could have a significant impact on driving behavior.

3.5. Distraction

This research [50] employed the EEG to examine the effects of different cognitive tasks (math and decision making problems) on drivers' cognitive state. Two simulated driving sessions, driving with distraction task and driving only, were designed to investigate the impact of a secondary task on EEG responses as well as the driving performance. They found that engaging the driver's cognitively with a secondary task significantly affected his/her driving performance as well as the judgment capability. They suggested that the activation in the right frontal cortex region may be considered the spatial index that indicated a driver who is in a state of cognitive distraction. In this study[51], they attempt to construct an EEG-based self-constructing neural fuzzy system to monitor and predict the driver's cognitive state. The experimental results including correlation and prediction show that the performances of the proposed system are significantly higher than using the traditional neural networks. In this study [52], they intend to examine the effect of the driving condition on the driver distraction as one aspect of the driver monitoring platform. Using our proposed driver monitoring platform, we study driver cognition under real driving task in two different road conditions including of peak and non-peak traffic periods. The experimental results illustrated that the power of theta and beta bands in the frontal cortex were substantially correlated with the road condition. Our investigations suggested that the features extracted from the time-frequency brain dynamics can be employed as statistical measures of the biometric indexes for early detection of driver distraction in real driving scenarios. The aim of the article [53] is to research how can visual smog influence the driver behavior. Part of the experiment was EEG device, used to record brainwave data during the testing of impact of visual smog to driver. The results regarding of driver gaze at visual smog are awful considering that the average dwell time of one billboard was more than a half second. On the other side, the average dwell time of traffic sign was only 0,2 second. In generally we can state that visual smog can influence the driver behavior which can lead to traffic accident**.** The present EEG study [54] investigated the effects of secondary acoustic and visual stimuli on driving performance of younger and older car drivers in a driving simulator task. The participants had to respond to brake lights of a preceding car under different distraction conditions and with varying task difficulties. In a more easy (perception only) task, simultaneously presented acoustic stimuli accelerated braking response times (RTs) in young and older adults, which was associated with a pronounced P2. In contrast, secondary visual stimuli increased braking RTs in older adults, associated with a reduced P3b. In a more difficult (discrimination) task, braking response behavior was impaired by the presence of secondary acoustic and visual stimuli in young and older drivers. Braking RT increased (and the P3b decreased), especially when the responses to the secondary stimuli had to be suppressed. The objective of this study [55] is to take a step toward establishing a systematic framework to extract effective descriptors and to measure the impact of in-vehicle secondary tasks on driver cognitive state during naturalistic driving by capturing the changes in EEG dynamics.. We present a standard analysis framework to examine the impact of various EEG signal pre-processing, feature extraction, and classification methods in order to detect driver engagement in a secondary task with high accuracy (98.99 ± 1.2%) solely based on their recorded EEG. In the this study [56] they assessed the effects of secondary cognitive task demand on eye movement and EEG metrics separately for periods prior to, during and after the hazard was visible. We found that when no hazard was present (prior and post hazard windows), distraction resulted in changes to various elements of saccadic eye movements. However, when the target was present, distraction did not affect eye movements.

3.6. Driving Style

The aim of this study[57] is to measure drivers' physiological and behavioral responses to road hazards and to extract features from measurements for further classification of risky and safe drivers. participants were classified into risky or safe drivers' group by applying only the 5 features. 81.82% and 77.78% accuracy of classification were attained for risky and safe drivers, respectively. The objective of the present work[58] was to identify electroencephalographic (EEG) components in order to distinguish between braking and accelerating intention in simulated car driving., source reconstruction showed that the dorso-mesial part of the 2 premotor cortex plays a key role in preparation of foot movement. Overall, the results illustrate that dorsomedial premotor areas are involved in movement preparation while driving, and that low-frequency EEG rhythms could be exploited to predict drivers' intention to brake or accelerate. This study[59] adopts two EEG analysis techniques (i.e., independent component analysis and brain source localization), two signal processing methods (i.e., power spectrum analysis and wavelets analysis) to extract twelve kinds of EEG features for the short-term driving state prediction. The prediction performance of driving features, EEG features and hybrid features of them was evaluated and compared. The results indicated that EEG-based model has better performance than driving-data-based model (i.e., 83.84% versus 71.59%) and the integrated model of driving features and the full brain regions features extracted by wavelet analysis outperforms other types of features with the highest accuracy of 86.27%. In this paper [60], they described that the driver's EEG during car following was decomposed by parallel factor analysis (PARAFAC), and they investigated the feature factor of longitudinal behavior for recognize and judgment from that decomposition result. They estimated the driver's intention from a driver's EEG using source current distribution estimation with Hierarchical Bayesian method and the sparse logistic regression. From the estimation results, the estimation accuracy of driver's intention was higher than about 70 % of three subject's in the lateral operation. To meet driving behavior based on imaging movements, in this study [61] an environment is designed integrated with audiovisual simulation, compared with arrows and other simple environments, the experimental data showed that the virtual one for the driving experience had been test well. In the experiment the initiative, immersion, focus attention and reducing visual fatigue have a unique advantage. For collecting and processing of EEG, the virtual environment has played a positive role. In this study [62] they collect data on ordinary driving behavior, including acceleration, space headway, speed, time headway, lane deviation, and amplitude of steering wheel movements. At the same time, the amplitude, log-transformed power (LTP), and power spectral density of EEG were extracted as EEG features. The results indicated that ordinary driving behavior relates to all four brain regions, especially the temporal, occipital, and frontal regions. b-LTP was found to be most relevant to ordinary driving behavior. Furthermore, acceleration, speed, and space headway may have potential correlation with EEG features (e.g., b-LTP). These findings improve our understanding of the correlation between brain activity and driving behavior, and show potential for application in transportation safety, such as advanced driver assistance systems design. This paper [63] aims to disclose the reliability of driving behavior in road traffic system. For this purpose, the drivers' electroencephalography (EEG) signals were collected with Emotive, a portable device, and used for an experiment in actual driving environment. The research results show that, with the increase in driving time, the intercity drivers became increasingly fatigued and their brain network continued to densify, pushing up the network parameters like clustering coefficient and global efficiency. In this case, the neuronal activities became increasingly synchronized across the brain regions. In addition, the two brain network parameters of the drivers were less discrete and more accurate than the fatigue indicator of EEG power spectrum features. Therefore, the analysis of brain network parameters is a precise and feasible method for discussing driving behavior reliability.

In this paper[64], they present analyzing brain activity using Muse, a wearable electroencephalography (EEG) brain band, and an ad-hoc Android smartphone application. Our study is focuses in a specific maneuver: the roundabouts, and in the comparison between the brainwaves produced in that handling and in a straight section. For this purpose, we made the same route in different moments of the day and under different weather conditions, and we isolate a specific stretch of six roundabouts and a straight one. Then we compare the beta and gamma brainwaves obtained in these two different maneuvers, which occurs in normal brain alert consciousness, attention or concentration states. The current research [65]aimed at validating the driving simulator from Beijing University of Technology in order to verify its usefulness in simulated experiment study based on the physiological signals. Researchers often account for behavioral validation through comparing speed and lane position of field and simulator. In this study, we compared the subject's electroencephalogram and electrocardiogram of field and simulator. Results showed that driving simulation is absolutely effectiveness in straight sections and large radius corners sections, and the index is not need calibrated, the data can be used as the experimental results. Otherwise, it is necessary to calibrate the index.

This paper [66] presents a novel and generic technique based on inducing identifiable signature pulses in data channels to accurately synchronise multiple temporal data streams. This technique is applied and its capabilities are exhibited using a driving game simulation as an exemplar. In this example, driver's ingame behavioural data is synchronised and correlated with their temporal brain activity. The concept of simplex method borrowed from linear programming is used to correlate between the driving patterns and brain activity in this initial study is provided so as to allow studying/investigating user behaviour in relation to learning of the driving track. The present study [67] aims to develop an efficient cross-subject transfer learning framework for driving status detection based on physiological signals. To grasp what part of knowledge was appropriate for transferring, cross-subject feature evaluation was used to measure feature quality.the experimental results revealed that the proposed algorithm could achieve high recognition accuracy and good transferability among individuals, which could increase the scope of application of physiological data for drive status detection during daily life, as it alleviated the need of subject specific pilot data for assessing the physiological characteristics across subjects. The present study [68] investigated the interplay of age, task workload, and mental effort using EEG measures and a proactive driving task. Steering variability and Theta power increased with increasing task load (i.e., with shaper bends of the road), while Alpha power decreased. This pattern of workload and mental effort was found in both age groups. However, only in the older group a relationship between steering variability and Theta power occurred: better steering performance was associated with higher Theta power, reflecting higher mental effort. Higher Theta power while driving was also associated with a stronger increase in reported subjective fatigue in the older group. In the younger group, lower steering variability came along with lower ERP responses to deviant sound stimuli, reflecting reduced processing of task18 irrelevant environmental stimuli.

In this paper [69] a method based on objective driving data and electroencephalography (EEG) data was presented to classify driving styles. The driving style of each participant was classified by clustering the driving data via K-means. Then the EEG data was denoised and the amplitude and the Power Spectral Density (PSD) of four frequency bands were extracted as the EEG features by Fast Fourier transform and Welch. Finally, the EEG features, combined with the classification results of the driving data were used to train a Support Vector Machine (SVM) model and a leave-one-subject out cross validation was utilized to evaluate the performance. The SVM classification accuracy was about 80.0%. Conservative drivers showed higher PSDs in the parietal and occipital areas in the alpha and beta bands, aggressive drivers showed higher PSD in the temporal area in the delta and theta bands. The present study [70] investigated the interaction of time on task, task load, and cognitive controllability in simulated driving scenarios, using an either re-active or pro-active driving task. Participants performed a lane-keeping task, half of them compensating varying levels of crosswind (re-active task), and the other half driving along a winding road (pro-active task). The results demonstrate that the controllability of a driving situation has a similar effect on oscillatory EEG activity like time on task and task load. In this study [71]Unity 3D was utilized to design the simulated driving scene. A photoelectric encoder fixed on the steering wheel and the corresponding data collection, transmission, and storage device was developed by Arduino, to acquire the rotation direction, angle, angular velocity, and angular acceleration of the steering wheel. Results indicated the significance of the cognitive state and seven personality traits [apprehension (O), rule consciousness (G), reasoning (B), emotional stability (C), liveliness (F), vigilance (L), and perfectionism (Q3)] in predicting driving behaviors, and the prediction accuracy was 80.2%. The negative and alert cognitive states were highly correlated with dangerous driving, including negative and violent behaviors. Personality traits complicate the relationship with driving behaviors, which may vary across different types of subjects and traffic accidents.

4. RECOMMENDATIONS

Several essential recommendations arise from the reviewed literature to further advance the application of EEG-based physiological signals in driver behavior monitoring systems. The researcher has classified them in this review into Monitoring cognitive workload, Data Collection, Decoding driver mental state, ADAS, and Human behavior and physiological factors.

1.1. Monitoring of Cognitive Workload

Drivers act various behaviors such as changing lanes, passing, making a U-turn, turning left and turning right in driving. Driver's workload is dependent on many factors such as driver's behavior, traffic flow, road types, driver's experience and etc. Driver's EEG is increased in excess of the 150km/h driving speed, steep downward slope and large radius of curve. Therefore, there is need for methods that drivers' workload according to behavior is measured and quantified[28]. Nonetheless, in order to provide services for safe and convenient driving, it is necessary to continue research on methods to measure the cognitive workload and predict the overload states of a driver[4]. The main cause of traffic accidents is drivers' human errors such as cognitive, judgment, and execution errors. To mitigate drivers' human errors, research on the measurement and quantification of driver workload as well as the development of smart vehicles is needed[72]. Thus, it should be noted that mental workload could become an indicator of the relational effectiveness between new technologies demands and human capacity. Thus, it emerges the need to design optimized vehicles where information systems aim to help driver, delegating their intervention to strategic decisions[73].

1.2. Data Collection

Driving simulator studies have dominated the research on driving mental fatigue mainly due to the safe, low cost, well-controlled conditions and ease of data collection. In addition, driving simulation allows the evaluation of a wider range of driving situations, especially those that are dangerous or physically threatening[74]. If EEG is to be measured in driving simulators, the environment preferably has to be electrically shielded in order to avoid amplified noise of, for instance, thecommon50Hz (in Europe). Measuring EEG, even in laboratory circumstances is relatively demanding with respect to skills and facilities[75]. Recording with a small number of channels means the system is closer to a practical solution in terms of physical electrodes attachment and computational complexity of the algorithm[1].In addition, the alert baseline EEG activity provides useful information for predicting inter-subject similarity in drowsiness-related brain responses. If so, one can select supportive source models based on easily collected baseline data from the target subject[76]. Fundamentally, the night before the experiment, the subjects are required to take enough sleep and are told not to drink coffee, alcohol or tea. None of them has a sleep disorder. When the subjects arrived for the experiment, the purpose of the study and experimental procedure are explained[77].

1.3. Decoding Driver Mental State

Since there is no uniform classification method suitable for all subjects and all applications, usually it may be useful to test and compare multiple classification methods. And considering some key factors (performance, complexity, flexibility, etc.) [77]. A subject-independent BCI could be achieved by a robust feature extraction method that reduces the inter-subject variability in the features used for decoding brain responses[76].
The Drowsiness Detection system based on the Driver's Operating Behavior needs to establish the driver's normal driving rule set and the non-normal driving rule set in advance[78]. In order to prevent drowsy driving, professional techniques need to be developed to prevent drowsiness related crashes by improving vehicle safety system, embedding within vehicle safety system drowsiness detection function[79]. Furthermore, to develop an accurate and non-invasive real-time driver drowsiness monitoring and prediction system would be highly desirable, particularly if this system can be further integrated into an automatic warning system[80].

1.4. ADAS

In the near future, once unsafe driving behavior has been identified, driver assistance systems will be able to send warnings to drivers and nearby vehicles[81]. Therefore, it is necessary that the driving assisting methods and the trigger timing of the driving assist technology should be set properly to fit the driver preferences and achieve the best cooperative characteristics. It is important to assess for the method how to fit the individual driver from measurable environment information, vehicle information and driver's information[82].

1.5. Human Behavior and Physiological Factors

Understanding the role that fatigue plays as a causal factor in road accidents is a critical first step towards better understanding, and thereby better managing, the risks associated with fatigue[83]. Continuous repetitive driving movements for a long time can lead to some physiological and psychological changes for drivers, and then affect their driving ability and alertness[84]. Road safety greatly depends on how drivers drive their vehicles. Their alertness is very significant to avoid crashes[85].The road rage may have an intensive impact on perception, planning, decision and maneuver of the drivers. In fact, an objectively ergonomic assessment of road rage is critically important for the analysis of driving behaviors[86]. To overcome the Road accidents driver behavior and the driving environment has to be monitored regularly and alert the driver before any accident may occur. This could be possible only on analyzing four measures: subjective, behavioral, physiological and vehicle-based. These combined hybrid measures can provide better accuracy on determining various states of driver like normal, drowsy, cognitive and visual inattention[87]

5. CONCLUSION

The intricacies of driving necessitate a blend of motor skills, visual acuity, heightened alertness, mental planning, and memory resources. While conventional studies have predominantly relied on subjective questionnaires and objective driving data for classifying driving behaviors, the utilization of physiological signals, particularly electroencephalography (EEG), remains underexplored. This research delves into EEG-based driver behavior monitoring systems, aiming to unravel the neuronal changes occurring during driving.
By systematically reviewing 70 articles sourced from reputable databases—IEEE, ScienceDirect, Web of Science, and PubMed—from 2010 to 2022, this study provides a comprehensive understanding of EEG's implications in monitoring driver behavior. The findings emphasize the challenges in depicting the full scope of EEG-based systems but underscore the significance of this integrated framework. This study not only offers clarity on technical and scientific aspects but also contributes state-of-the-art data acquisition and processing techniques, fostering a foundation for future

advancements in EEG-based driver monitoring systems. In essence, the research contributes to a nuanced comprehension of the subject matter, offering valuable insights into addressing the complexities embedded in the academic literature.

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