AIMSafe: EEG-Based Driver Behavior Understanding via Attention and Incremental Learning Mechanisms

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Abstract. In this paper, we propose *AIMSafe*, an electroencephalographic (EEG) based system that studies driver in-vehicle behaviors leveraging **A**ttention networks and **I**ncremental learning **M**echanism for road **Safe**ty. Instead of using predefined classes, we categorize driver in-vehicle activities into different risk levels - a stronger motion may have a higher chance of unsafe driving. More specifically, we first employ a CNN based model to distinguish two basic activities - 1. normal driving and 2. unsafe driving. Moreover, *AIMSafe* also leverages smartphone IMU sensors generating soft hints that helps automatically label EEG data on road. We then adopt class-incremental learning to rank other Out-of-Distribution (OOD) driver activities (safe to unsafe) based on the Mahalanobis distance. A modified Squeeze-and-Excitation (SE) block is also used to adaptively select effective EEG electrodes for improving the system efficiency. Evaluation results (involving 11 males and 4 females) show that *AIMSafe* could achieve a detection accuracy over 95% on unsafe driving activities using only 4 electrodes.

Keywords: Driving Safety · Driver Education · Wearable Sensing · EEG · Smart computing

1 Introduction

Driver inattention/distraction is a major factor causing a great number of traffic accidents every year. Driven by a pressing need to enhance road safety, many advanced systems have been developed as high-tech features in today's cars to monitor driver status by using specialized cameras or infrared sensors [1]. What's more, efforts have been made to explore smart sensing technologies for safe driving study and traffic congestion analysis [7,28]. For example, wrist-worn devices (e.g., smartwatch) are used for driver hand motion tracking and forearm posture recognition [6,14,25]. In addition, recent Wi-Fi CSI (channel state information)

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and acoustic (ultrasonic) based systems have seen great success in human in-vehicle activity recognition [20,24].

On the other hand, electroencephalogram (EEG) has been gaining great attention in various fields such as medical diagnosis, cognitive enhancement, entertainment and education. EEG devices have become more lightweight, wearable, affordable and efficient, which increased the popularity and acceptance in different applications. A number of EEG based driving safety systems have been proposed, they mainly focus on the detection of unsafe/inattentive driving periods like drowsy and non-drowsy [8,10,30], distracted and non-distracted [27]. Though some work used EEG signals to indentify visual distracting conditions such as reading smartphone [5], viewing navigation [26] as well as visual/cognitive [17]. However, there are still a great number of common in-vehicle activities that may cause unsafe driving, while existing work can not address them all due to limited types of predefined activities.

Moving along this direction, instead of classifying EEG signals elicited by predefined driver behaviors, we aim to provide a more general model that evaluates driver behaviors with different driving risk levels. It is based on the hypothesis that a driver will have stronger movements when encountering unsafe driving conditions (e.g., reaching the back seat), which may result a more noticeable stimuli in EEG patterns. While drivers may perform various motion styles (e.g., direction and speed) that imprint unique hallmarks in EEG signals. We are unable to label all possible types of events/behaviors for classification/recognition. Alerts based on risk levels could give drivers proper feedbacks and help them shape good driving habits, and thus avoid potential traffic accidents.

To achieve the goal, in this paper we propose *AIMSafe*, an EEG based driver **Safe**ty system that leverages **A**ttention networks and **I**ncremental learning **M**echanism. Specifically, we first use a Convolutional Neural Network (CNN) model to indentify two basic driver activities - 1. holding the steering wheel as normal driving - the least significant movement (safe), and 2. rotate the head and arm to reach the back seat - the most significant movement (unsafe). *AIMSafe* also utilizes smartphone IMU sensors that generates soft hints to detect vehicle turning events. We then adopt an incremental learning method using Mahalanobis distance to adaptively rank any other new in-vehicle activities without further model training [16]. Furthermore, *AIMSafe* employs a modified attentive squeeze-and-excitation (SE) block producing a collection of per-channel modulation weights. The main contributions of this paper are summarized as follows:

1. We propose *AIMSafe*, an EEG based approach for understanding driver behaviors in a cost-effective way. The system is able to detect and alert different types of most commonly occurring in-vehicle driving activities based on risk levels, which can be used in training courses to educate and help driver shape good driving habits.
2. We explore time-frequency features of EEG signals and propose a CNN model with modified attentive Squeeze-and-Excitation Networks to recognize basic in-vehicle activities and perform channel (electrode) selection. An adaptive

turning event labelling method is also provided by piggybacking on vehicle dynamic sensing using smartphone IMU sensors. We then employ the Mahalanobis distance-based incremental learning method to further indentify new OOD samples.

3. We design and build experimental environments involving 15 participants in stationary and moving vehicles. In the evaluation, AIMSafe achieved the accuracy of 100% using 4 electrodes for basic-activity classification, while the overall detection accuracy of OOD samples is over 95%. Which demonstrate that the proposed solution is robust and effective to indentify in-vehicle unsafe activities and has great potential to promote driving safety.

The reminder of the paper is organized as follows. Section 1 discusses the motivation and design considerations of implementing the proposed system. Section 2 gives a brief description of AIMSafe design and implementation details of the system. Sections 3 presents the experiments in real vehicles as well as the evaluation results, we further discusses how this work can be extended and how to improve the system performance. Section 4 reviews the related work on driver distraction study and Sect. 5 concludes the paper.

2 System Design

2.1 System Overview

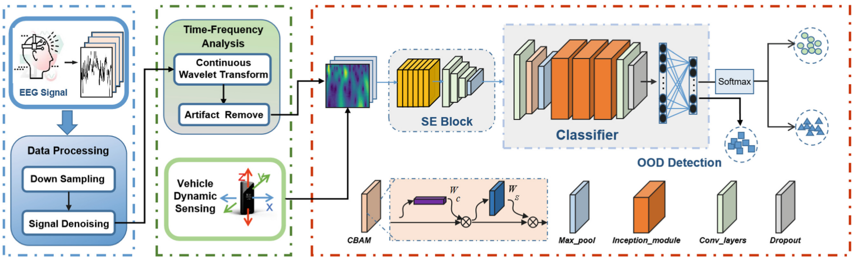

Fig. 1. System Overview

In this paper, instead of classifying a limited number of pre-defined driving event, we aim to help drivers to be aware of the risk levels of their in-vehicle behaviors. We divide these in-vehicle activities into 3 categories: 1. safe - normal driving, 2. potential dangerous - Secondary Tasks (unsafe when it takes more than 3 seconds), 3. dangerous - unsafe/strong motion. More specifically, AIMSafe is comprised of several key components including **Data collection and preprocessing**, **Time-frequency analysis and vehicle dynamic sensing**, **Human motion spotting and classification** and **Driver activity classification and OOD sample identification**. As illustrated in Fig. 1, these four components work together to continuously monitor the driver's in-vehicle activities and identify any instances of distracted or unsafe behavior. The system uses advanced signal processing and a lightweight version of Inception CNN mode to analyze EEG signals and provide real-time alerts to the driver if necessary.

2.2 EEG Data Collection and Preprocessing

Data Formatting. To improve the computational efficiency of driving distraction detection, we need to select the most representative channels from the 32 EEG electrodes available. Based on EEG studies of driver behavior analysis [2,21], we have selected 16 electrodes for this purpose, including FP1, F7, FZ, FC2, T7, C3, C4, CZ, CP1, CP2, P7, F5, PZ, O1, FC4, and O2. We will further reduce this number to 8 using a modified SE block in the classification module, and then further down to 4, and finally to 2. We will compare the performance of different sets of electrode selections.

To record the data, we have used a sliding window of 2 seconds with a 1-second stride at a sampling rate of 250 Hz. Moreover, we also leverage driver smartphone IMU sensors to detect turning events, while at the same time automatically label the EEG data during this time period. Then we are able to measure a baseline of target driver motion strength (turning the steering wheel is a necessary task to operate a vehicle).

Time-Frequency Analysis. EEG data is a collection of non-stationary time series corresponding to measurements of human brain activities across different frequency bands over each electrode, thus a transformation to the time-frequency domain is necessary for feature extraction. For the non-stationary time series, in signal processing, comprises a set of techniques studying signal representation in time-frequency domains. Among various methods, Wavelet transform (WT) outperformed others in recent CSI based human motion detection research [19]. WT methods (known as discrete or continuous WT) allow multi-resolution signal analysis at different scale components by using a mother wavelet function. It shows excellent advantages for the analysis of transient signals like EEG, Wi-Fi CSI, etc. In this paper, we use cgau8 as the kernel and set scale range 1–64, thus output a 64×500 $(250 \times 2) \times 16$ (channels) data matrix (spectrogram) of each window. In addition, since the eye states information is also very important for driver behavior analysis, we extract it as back up data/hints for the future study. After eye movements removal, the data size become 48 (frequency) $\times$ 500 (time/samples) $\times$ 16 (channels).

2.3 Human Motion Spotting

Driver Specific Feature Extraction with SE Block. With the increase in the depth and width of neural networks, the number of parameters and computational cost has also increased. To address this issue, we utilize the Squeeze-and-Excitation (SE) block [11] to address the issue of channel reduction. The SE block is a lightweight and efficient module that can be easily integrated into existing neural networks. The block consists of two operations: Squeeze and Excitation, as shown in Fig. 2. The Squeeze operation takes an input feature map and generates a channel descriptor by aggregating global spatial information using global average pooling. The Excitation operation then takes the channel descriptor as input and produces a collection of per-channel modulation weights.

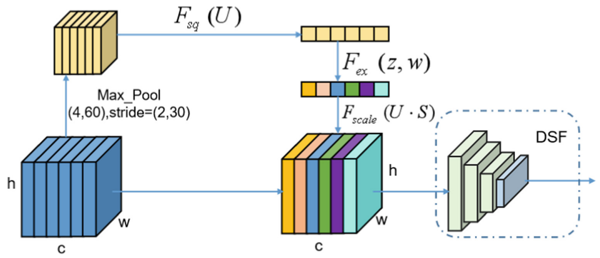

Fig. 2. SE BLock based Driver Specific Feature extraction

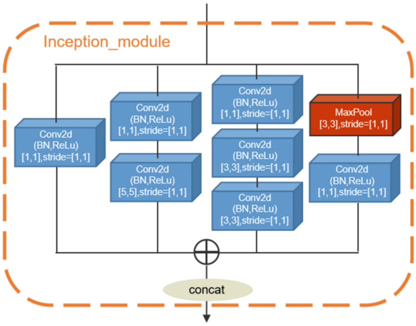

Fig. 3. Inception Network Structure

While traditional SE block has been successfully used in various deep learning models and EEG-based studies, it cannot be directly applied for EEG channel reduction as the existing SE block structure is designed to adjust the weights of feature maps (e.g., the output of a convolution layer), which erases the tags of EEG channels (electrodes). Although we can remove the transformation and directly connect the input matrix to SE block, the global pooling operation used to generate the channel descriptors in SE block may cause loss of spatial information (H×W), which is important for EEG analysis due to the distribution of brain signals following a Gaussian distribution with the global average value close to zero. To address this issue, we propose to use a Max Pooling layer to extract local maximums as features and then feed them to the SE block. The weights of each EEG channel can then be updated during training via backpropagation.

Inception Based Classification Module. We evaluated several networks with varying numbers of layers to draw conclusions, which were largely based on empirical observations. After thorough experimentation, we arrived at a modified, lightweight version of the Inception V3 model shown in Fig. 3. Which was achieved through modifications of the previous Inception Networks [22]. Additionally, it has been shown that the Squeeze-and-Excitation (SE) block can improve performance when integrated with Inception models. Therefore, we plan to explore the use of this network in future work for EEG signal analysis.

2.4 Mahalanobis Distance Based Incremental Learning

During real driving scenario, the method of combining incremental learning with Mahalanobis distance can dynamically update the hazard rating to adapt to the constantly changing environment while accumulating new data. To further distinguish different driver behavior based on their motion levels, we consider measuring the Mahalanobis distance from the output of the penultimate layer of Neural Network. We get the Gaussian distribution of basic category from the pre-trained softmax neural classifier, Therefore, we could compute the empirical class mean $\hat{\mu}_c = \frac{1}{N}\sum_{i:y_i=c} f(x_i)$ and covariance of training samples as:

$$Cov_c = \sum_{i:y_i=c} (f(x_i) - \hat{\mu}_c)(f(x_i) - \hat{\mu}_c)^T \tag{1}$$

where $f(x_i)$ is the latent output of neural network, $\hat{\mu}_c$ is the mean of training samples with label c.

Using Gaussian distribution of basic categories, we define $M(x)$ between test sample x and existing label c to estimate the degree of danger.

$$M(x) = (f(x) - \hat{\mu}_c)^T Cov_c(f(x) - \hat{\mu}_c) \tag{2}$$

where N is the number of training samples of each class with label C. By using the mean vector and covariance matrix above, we are able to calculate the Mahalanobis distance of each OOD driver behavior to the basic classes. We then input the EEG data of driver doing steering wheel turning (automatically recorded) to calculate the Mahalanobis distance between normal driving and unsafe driving - feature extracted by the Inception model. The mean value of the distance can be used as the boundaries to categorize driver activities into different groups based on their motion level.

3 Evaluation

3.1 Experimental Setup and Data Collection

We use a wireless EEG headset from Guger Technologies (model name: g.Nautilus RESEARCH Headset) to collect brain activity data. We recruited 15 participants - 4 females and 11 males from age 19 to 50. Each participant was asked to perform 4 target types of activities in real vehicles. When recording the data of normal driving behavior, participants were asked to drive the vehicle at a lower speed (less than 30 KM/h) on the same selected driving route (2.0 KM). In contrast, when participants are required to perform some unsafe driving behaviors, they will sit in the front passenger's seat (with a steering wheel of a simulator), record data on the driving vehicle, and simulate the driver's behavior in the real road as much as possible. In summary, one participant was asked to perform at least 200 times of each type of gesture (100 in the parking lot and 100 on real road). The cross validation (60% training and 40% testing) is also applicable due to the limited number of samples.

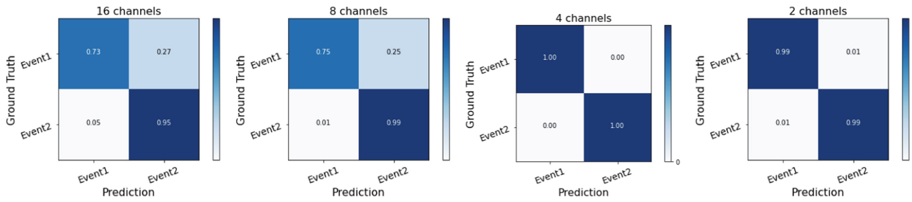

Fig. 4. Model performance on base classes with 16, 8, 4 and 2 channels

3.2 Unsafe Driving Detection

In this section, we provide a comprehensive analysis to examine the performance of proposed models. We also define the metrics including True Positive (number of driving activities that are correctly identified), False Positive (number of driving activities are wrongly classified) and detection rate/accuracy (number of correctly detected testing samples).

Base Class Recognition. Figure 4 shows that the proposed model using 4 ('FC2', 'CP1', 'CP2' and 'F5') and 2 ('FC2' and 'CP2') channels/electrodes achieved the very high average accuracy (over 99%) distinguishing two base classes. Though two base motion classes are significant different in real physical world, noise and diverse among drivers under different driving conditions (as we claimed) resulting complex EEG signal patterns - lower accuracy in 16 and 8 channels. According to these results, we select 4 channel (highest accuracy) as the default setting for later test since it can be more stable if there is a variety of new challenging scenarios (vehicles and drivers) in the future.

Incremental Learning Result Analysis. In Fig. 5, we present the outputs of Mahalanobis distance based method with 2 selected participants (1 male and 1 female). As we can see from 2 figures, the distance distributions of each participant are similar but at the same time the value patterns are quite different - one may have stronger motion and other may have more frequent movements. For instance, "Turnback" is consistently one of the actions with the highest magnitude and highest risk across all the charts. Meanwhile, we can observe that normal turning events, indicated by the baseline (blue), effectively differentiate between safe (holding the steering wheel and secondary tasks) and potentially

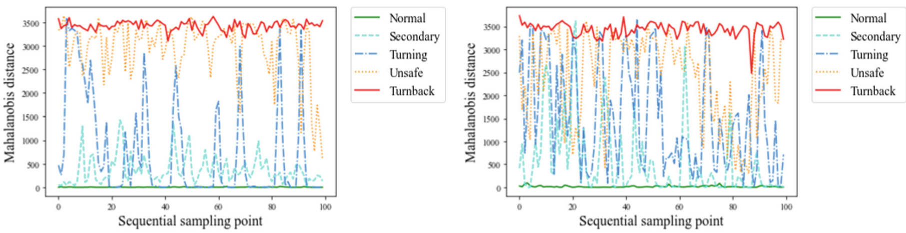

Fig. 5. Mahalanobis distance of each behavior from selected participants (Color figure online)

unsafe events. While some users exhibit clear data curves, while for others, the curves are blurry. Therefore, more effective machine learning methods are needed to differentiate them.

Table 1. 2-second Mahalanobis Distance

People	Event							
	Normal		Secondary		Unsafe		Turnback	
	P	D	P	D	P	D	P	D
user1	0.00	0.03	0.32	0.51	0.94	0.99	1.00	1.00
user2	0.00	0.00	0.64	0.75	0.96	0.99	1.00	1.00
user3	0.02	0.02	0.68	0.75	0.98	1.00	1.00	1.00
user4	0.05	0.05	0.46	0.48	0.93	0.96	1.00	1.00
user5	0.00	0.00	0.02	0.08	0.96	0.99	1.00	1.00
user6	0.00	0.00	0.21	0.43	0.99	1.00	1.00	1.00
Average	0.01	0.02	0.39	0.50	0.96	0.99	1.00	1.00

What's more, we test and compare the performance of learning model using Mahalanobis Distance and Euclidean Distance for each user. As illustrated in Table 1 and Table 2, we choose a 2-second time window for driving event detection, as the shorter time window could alert driver earlier (3 seconds rule). Where P and D in tables mean potential dangerous (counting 3 seconds) and dangerous. We can see that the Normal driving events never exceed the line of dangerous and sometimes detected as potential dangerous. For secondary tasks, the detection rate is from 30% to 90% as a potential dangerous task. It is because that drivers has to move their body and arms back and forth due to different tasks, the Mahalanobis distance are not always beyond the threshold and over the dangerous line occasionally (may be False Positive). And for unsafe behaviors and turnback events, our method could achieve a high detection rate (over 95% on average).

Table 2. 2-second Euclidean Distance

People	Event							
	Normal		Secondary		Unsafe		Turnback	
	P	D	P	D	P	D	P	D
user1	0.00	0.00	0.22	0.17	0.88	0.86	1.00	1.00
user2	0.00	0.00	0.57	0.50	0.98	0.98	1.00	1.00
user3	0.00	0.00	0.43	0.28	0.93	0.81	1.00	1.00
user4	0.01	0.00	0.38	0.22	0.91	0.79	1.00	1.00
user5	0.00	0.00	0.00	0.00	0.97	0.96	1.00	1.00
user6	0.00	0.00	0.18	0.26	1.00	1.00	1.00	1.00
Average	0.00	0.00	0.30	0.24	0.95	0.90	1.00	1.00

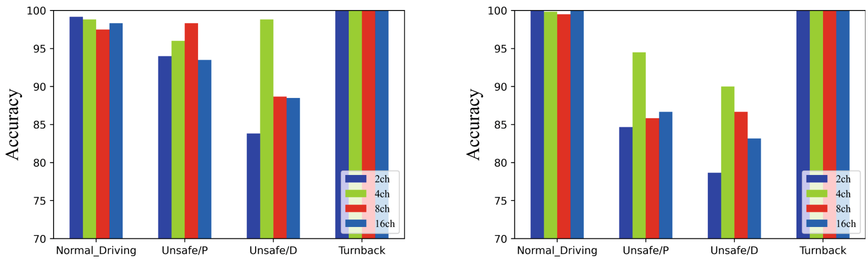

Fig. 6. Accuracy based on Mahalanobis distance and Euclidean distance

Moreover, we also evaluated the average performance of two distance metrics - Mahalanobis distance and Euclidean distance, in detecting unsafe driving activities using different channel settings with the time window length - 2 seconds. The detection accuracy comparison between the two metrics is presented Fig. 6. It can be observed from the figures that the system accuracy of using Mahalanobis distance is higher than using Euclidean distance for detecting unsafe driving activities, especially in the case of using 4-channel settings. This suggests that Mahalanobis distance is a more suitable metric for accurately detecting unsafe driving activities using EEG signals, as it takes into account the correlation among the EEG channels. It highlight the importance of choosing an appropriate distance metric when analyzing EEG signals for detecting unsafe driving activities, and we will take the Mahalanobis distance as the criterion in the subsequent experiments.

4 Related Work

In this section, we focus on reviewing mainstream schemes on smart sensing-based approaches for driving activity (distractions) monitoring. By taking the advantage of computer vision techniques, there has been active research work for detecting inattentive or distracted driving problems. Jiang et al. [13] propose a smartphone based system to detect unsafe events at intersections such as running red lights, running stop signs, unsafe turns, etc. Moreover, a number of vision based systems leveraging the deep learning models are presented for distraction driving detection [3,23]. Meanwhile, there are several smart-sensor based systems tracking driver hands position for preventing unsafe driving activities [9]. Bi et al. [6] presented SafeWatch, a system using smartphone and smartwatches to estimate the posture of the driver's forearms and hands. Johnson et al. [15] also works on locating a smartphone in the vehicle using the acquired motion data when a user is holding it. Jiang et al. [14] focuses on driver's right hand motion to recognize secondary tasks and potential dangerous behaviors.

Many device-free systems using wireless or acoustic signals for driver behavior monitoring have been offered. Xu et al. [29] leveraged existing audio devices on smartphones to realize early recognition of inattentive driving events. Jiang et al. [12] proposed DriverSonar, a system that targets driver head motions such as nodding, yawning and adjust abnormal steering of commercial vehicles. What's more, using Wi-Fi channel state information (CSI) for driver motion sensing are gaining popularity. WiCAR [24] employed a multi-adversarial domain adaptation network model to recognize various driver inattentive activities, while Bai et al. [4] proposed a feature combination solution named CARIN to detect a series of common driver gestures and perform well in real-car setting scenarios. Although above methods achieved promising results, they are susceptible to the change of testing environments, the extra infrastructure cost should be also considered.

Early eeg based approaches mainly focus on determining the periods of driver drowsiness (drowsy or non-drowsy) and distraction (distracted and non-distracted) by exploring the correlation between EEG data and driver eye/head states [18,26]. Towards the most recent work in detecting driver behaviors, Bajwa et al. [5] presented a study on distraction stimuli by using EEG signals to record unsafe driving events such as reading, texting, and using phone cameras. Li et al. [17] further investigate EEG patterns by employing both CNN models and gated recurrent units (GRUs) on different types of driver distractions including cellphone operation task, clock task, and 2-back task. Unlike above EEG based approaches, in this paper we aim to identify distracted activities that most commonly occurred in the vehicle. To the best of our knowledge, it is the first work that leverages EEG signals targeting certain in-vehicle driver manual distractions. More importantly, we also propose a channel reduction scheme to select most representative electrodes, which could achieve a comparable accuracy (using only 2 electrodes) with much lower computational cost compare to existing solutions (e.g., 32 or 16 channel electrodes).

5 Conclusion

In this paper, we aim to build a EEG based sensing system that detects most common occurring distracted driving events. AIMSafe can actively records a number of in-vehicle distracting activities and the overall performance is promising. Moreover, we focus on the task of active human motion detection and channel reduction solutions, which is a stepping stone to general multi-channel time series data analysis. In the future, we tend to solve the above-mentioned limitations and enhance system performance with several possible solutions.

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References

1. Al-Sultan, S., Al-Bayatti, A.H., Zedan, H.: Context-aware driver behavior detection system in intelligent transportation systems. IEEE Trans. Veh. Technol. **62**(9), 4264–4275 (2013)
2. Alomari, M.H., Baniyounes, A.M., Awada, E.A.: EEG-based classification of imagined fists movements using machine learning and wavelet transform analysis. Int. J. Adv. Electron. Electr. Eng. **3**(3), 83–87 (2014)
3. Assefa, A.A., Wenhong, T.: Bio-mechanical distracted driver recognition based on stacked autoencoder and convolutional neural network. In: 2019 IEEE 2nd International Conference on Information Communication and Signal Processing, pp. 449–453. IEEE (2019)
4. Bai, Y., Wang, X.: CARIN: wireless CSI-based driver activity recognition under the interference of passengers. Proc. ACM Interact. Mob. Wearable Ubiquit. Technol. **4**(1), 1–28 (2020)
5. Bajwa, G., Fazeen, M., Dantu, R.: Detecting driver distraction using stimuli-response EEG analysis. arXiv preprint arXiv:1904.09100 (2019)
6. Bi, C., Huang, J., Xing, G., Jiang, L., Liu, X., Chen, M.: SafeWatch: a wearable hand motion tracking system for improving driving safety. ACM Trans. Cyber-Phys. Syst. **4**(1), 1–21 (2019)
7. Chen, D., Cho, K.T., Han, S., Jin, Z., Shin, K.G.: Invisible sensing of vehicle steering with smartphones. In: Proceedings of the 13th Annual International Conference on Mobile Systems, Applications, and Services, pp. 1–13 (2015)
8. Chuang, C.H., Huang, C.S., Ko, L.W., Lin, C.T.: An EEG-based perceptual function integration network for application to drowsy driving. Knowl.-Based Syst. **80**, 143–152 (2015)
9. Goel, B., Dey, A.K., Bharti, P., Ahmed, K.B., Chellappan, S.: Detecting distracted driving using a wrist-worn wearable. In: 2018 IEEE International Conference on Pervasive Computing and Communications Workshops, pp. 233–238. IEEE (2018)
10. Gurudath, N., Riley, H.B.: Drowsy driving detection by EEG analysis using wavelet transform and k-means clustering. Procedia Comput. Sci. **34**, 400–409 (2014)
11. Hu, J., Shen, L., Sun, G.: Squeeze-and-excitation networks. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 7132–7141 (2018)
12. Jiang, H., Hu, J., Liu, D., Xiong, J., Cai, M.: DriverSonar: fine-grained dangerous driving detection using active sonar. Proc. ACM Interact. Mob. Wearable Ubiquit. Technol. **5**(3), 1–22 (2021)
13. Jiang, L., Chen, X., He, W.: SafeCam: analyzing intersection-related driver behaviors using multi-sensor smartphones. In: 2016 IEEE International Conference on Pervasive Computing and Communications (PerCom), pp. 1–9. IEEE (2016)

14. Jiang, L., Lin, X., Liu, X., Bi, C., Xing, G.: SafeDrive: detecting distracted driving behaviors using wrist-worn devices. Proc. ACM Interact. Mob. Wearable Ubiquit. Technol. **1**(4), 1–22 (2018)
15. Johnson, G., Rajamani, R.: Smartphone localization inside a moving car for prevention of distracted driving. Veh. Syst. Dyn. **58**(2), 290–306 (2020)
16. Lee, K., Lee, K., Lee, H., Shin, J.: A simple unified framework for detecting out-of-distribution samples and adversarial attacks. In: Advances in Neural Information Processing Systems, vol. 31 (2018)
17. Li, G., Yan, W., Li, S., Qu, X., Chu, W., Cao, D.: A temporal-spatial deep learning approach for driver distraction detection based on EEG signals. IEEE Trans. Autom. Sci. Eng. **19**(4), 2665–2677 (2021)
18. Narejo, S., Pasero, E., Kulsoom, F.: EEG based eye state classification using deep belief network and stacked autoencoder. Int. J. Electr. Comput. Eng. (IJECE) **6**(6), 3131–3141 (2016)
19. Palipana, S., Rojas, D., Agrawal, P., Pesch, D.: FallDeFi: ubiquitous fall detection using commodity Wi-Fi devices. Proc. ACM Interact. Mob. Wearable Ubiquit. Technol. **1**(4), 155 (2018)
20. Raja, M., Ghaderi, V., Sigg, S.: WiBot! In-vehicle behaviour and gesture recognition using wireless network edge. In: 2018 IEEE 38th International Conference on Distributed Computing Systems (ICDCS), pp. 376–387. IEEE (2018)
21. Suwannarat, A., Pan-ngum, S., Israsena, P.: Comparison of EEG measurement of upper limb movement in motor imagery training system. Biomed. Eng. Online **17**(1), 103 (2018)
22. Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J., Wojna, Z.: Rethinking the inception architecture for computer vision. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 2818–2826 (2016)
23. Torres, R., Ohashi, O., Carvalho, E., Pessin, G.: A deep learning approach to detect distracted drivers using a mobile phone. In: Lintas, A., Rovetta, S., Verschure, P.F.M.J., Villa, A.E.P. (eds.) ICANN 2017. LNCS, vol. 10614, pp. 72–79. Springer, Cham (2017). https://doi.org/10.1007/978-3-319-68612-7_9
24. Wang, F., Liu, J., Gong, W.: WiCAR: WiFi-based in-car activity recognition with multi-adversarial domain adaptation. In: 2019 IEEE/ACM 27th International Symposium on Quality of Service, pp. 1–10 (2019)
25. Wang, L., Gu, T., Chen, H., Tao, X., Lu, J.: Real-time activity recognition in wireless body sensor networks: from simple gestures to complex activities. In: 2010 IEEE 16th International Conference on Embedded and Real-Time Computing Systems and Applications, pp. 43–52. IEEE (2010)
26. Wang, S., Zhang, Y., Wu, C., Darvas, F., Chaovalitwongse, W.A.: Online prediction of driver distraction based on brain activity patterns. IEEE Trans. Intell. Transp. Syst. **16**(1), 136–150 (2014)
27. Wang, Y.K., Jung, T.P., Lin, C.T.: EEG-based attention tracking during distracted driving. IEEE Trans. Neural Syst. Rehabil. Eng. **23**(6), 1085–1094 (2015)
28. Wang, Y., Cao, J., Li, W., Gu, T., Shi, W.: Exploring traffic congestion correlation from multiple data sources. Pervasive Mob. Comput. **41**, 470–483 (2017)
29. Xu, X., et al.: ER: early recognition of inattentive driving leveraging audio devices on smartphones. In: IEEE Conference on Computer Communications, pp. 1–9 (2017)
30. Yang, Y., Du, Z., Jiao, F., Pan, F.: Analysis of EEG characteristics of drivers and driving safety in undersea tunnel. Int. J. Environ. Res. Public Health **18**(18), 9810 (2021)