Attention Classification of Drivers Using Convolutional Neural Networks

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Introduction

Evidence points toward the leading role of driver inattention and fatigue in car accidents (Rosenbloom et al., 2008). This issue calls for the development of brain-computer interface (BCI) systems able to detect and prevent such inattentive behavior. Past studies have mainly employed Machine Learning (ML) models on users' EEG activity to classify their attention state (Abbas & Alsheddy, 2021). This approach relies on feature extraction from EEG signals (e.g. spectral band powers), which requires time-consuming pre-processing, entails loss of information and ultimately depends on the human expertise in selecting the task-relevant features (Tibrewal et al., 2021). Deep Learning (DL) models such as convolutional neural networks (CNN) could alleviate this issue as they extract optimal features from raw EEG signals on their own and facilitate end-to-end learning (Li et al., 2018).

Other key challenges in applying BCIs in real-world scenarios include subject-specific calibration and ecological validity of the task during data collection (Allison et al., 2012). In an operational environment such as driving, calibrating the BCI classifier for each subject is often not feasible. A potential solution could be subject-independent classifiers in which the data of many individuals is used for training of the model (Fazli et al., 2009; Zhang et al., 2019). Furthermore, in real-world driving, drivers have access to a battery of sensory information, which could impact attention and thus brain activity (Chuang et al., 2014; Lin et al., 2010). Therefore, lab experiments should employ realistic settings such as virtual simulators in which visual and kinesthetic feedback are provided and their impact on the drivers' BCI performance are measured in an ecologically valid way.

This study addresses the above challenges in the state-of-the-art attention BCIs by comparing the performance of a CNN classifier to SVM in a simulated driving setting. In addition to the role of EEG activity type (raw signal vs. spectral features), we explored the impact of kinesthetic feedback (with vs. without feedback) and classification approach (mixed-subject vs. inter-subject) on model performances.

Method

A public dataset was used in this study (Cao et al., 2019). Fourteen subjects performed a driving task in an immersive simulator while the car randomly deviated from the cruising lane (Fig. 1a). Each subject took part in two conditions: one in which they received realistic kinaesthetic feedback from the car simulator (K+) and another where they did not (K-). Their brain activity was measured using EEG over 30 channels at a sampling rate of 500 Hz (Fig. 1b). The data was marked with the timing of deviations (deviation onset) and the time it took the subject to correct the deviation (reaction time). EEG activity in a 3-sec window before the deviation was chosen as classifier input for attention state detection. The reaction time associated to that deviation was used to label the EEG segment as either attentive or inattentive.

Two models were compared in this study. First, a compact CNN called EEGNet (Lawhern et al., 2018) was trained in two ways; 1) on the raw EEG data and 2) on spectral band powers extracted from the EEGs. These included delta (0-4 Hz), theta (4-7 Hz), alpha (8-12 Hz), beta (12-30 Hz), and gamma (30+ Hz) bands. Next, a support vector machine (SVM) was trained on only these five frequency band powers.

Both models were trained and tested using two approaches. In one approach, samples from all subjects were mixed together and used to train the model using 5-fold cross-validation (mixed-subject approach). In the other approach, samples from each subject were kept separate and used in leave-one-

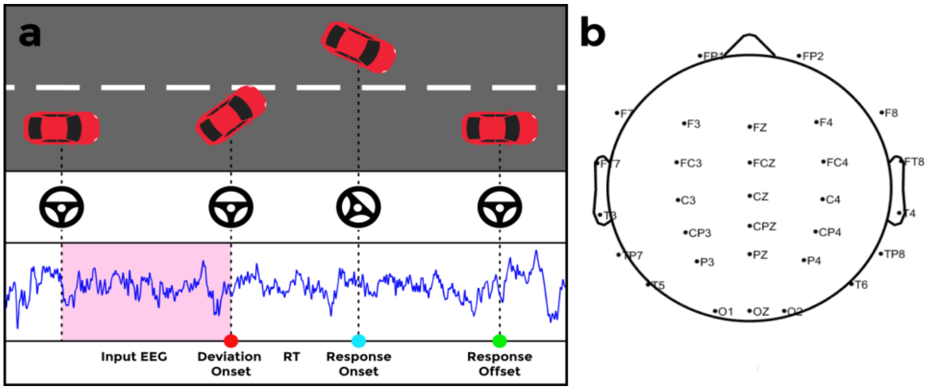

Figure 1. Experimental design. (a) Subjects were instructed to drive a car within lane in a virtual simulator. During the task, the car would randomly deviate from the road (deviation onset). Subjects had to correct the deviation as fast as possible by steering back onto the correct road (response onset). EEG activity prior to deviation onset and reaction times were used as training data and classification labels. (b) Layout of the 30 electrode channels used in EEG recording.

subject-out cross validation (inter-subject approach). This method is akin to inter-subject transfer learning as shown in other attention classification studies (Liu et al., 2020).

Results and Discussion

Table 1 summarizes the performance of SVM and EEGNet models in two approaches and different feedback conditions. The highest accuracy (89%) was achieved by EEGNet when it was trained on raw EEG activity in the mixed-subject approach and drivers received kinaesthetic feedback (K+). Several isolated comparisons can be made based on Table 1. First, when drivers received kinaesthetic feedback, EEGNet performed best, while without feedback, SVM performed best. This unexpected contrast could be explained by the complexity of the information from the simulator environment. With kinaesthetic feedback, drivers have to process richer sensory information, which is reflected on their EEG activity. CNN can extract relevant features better from this complex data, while SVM performs better with EEG features underlying simpler events. Second, using mixed-subject data always led to better classification performances over inter-subject data. This was not surprising, as the classifier has seen examples of the subject’s brain activity in the training phase. Nevertheless, the inter-subject approach achieved a maximum accuracy of 77% using SVM. This is similar to state-of-the-art reports that applied inter-subject transfer learning (Fahimi et al., 2019; Liu et al., 2020), suggesting the possibility of a universal attention BCI that does not require calibration for new users.

While this study only performed offline classification, our results encourage future research to examine the potential of CNNs in online attention classifiers. Using raw EEG signals from multiple subjects, researcher can save resources in data collection and model calibration. Moreover, CNN is likely to perform better than the often-used ML models as real-world environments contain far more sensory information than laboratory settings. Overall, this research can be helpful in development of passive BCI systems, as well as driver assistance systems aiming to improve road safety.

Table 1. Accuracies of the deep learning (EEGNet) and machine learning (SVM) models trained on mixed-subject and inter-subject data while subjects received either kinaesthetic feedback (K+) or no feedback (K-).

Model	**Mixed-Subject**		**Inter-Subject**	
	K+	***K-***	***K+***	***K-***
SVM	82.46	85.71	69.73	77.20
EEGNet using spectral bands	83.12	80.52	68.80	71.75
EEGNet using raw EEG	**88.96**	81.82	75.51	69.35

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