Using Pre-stimulus EEG to Predict Driver Reaction Time To Road Events

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Abstract— **The ability to predict a driver's reaction time to road events could be used in driver safety assistance systems, allowing for autonomous control when a driver may be about to react with sup-optimal performance. In this paper, we evaluate a number of machine learning and feature engineering strategies that we use to predict the reaction time(s) of 24 drivers to road events using EEG (Electroencephalography) captured in an immersive driving simulator. Subject-independent models are trained and evaluated using EEG features extracted from time periods that precede the road events that we predict the reaction times for. Our paper has two contributions: 1) we predict the reaction times corresponding to individual road events using EEG spectral features from a time period before the onset of the road event, i.e. we take EEG data from 2 seconds before the event, and 2) we predict whether a subject will be a slow or fast responder compared to other drivers.**

I. INTRODUCTION

Mental fatigue and drowsiness are the main causes of road accidents worldwide [1], and are often the result of sleep deprivation and/or focusing on a task for a long period of time [2]. Similarly, slow reaction times to events on the road can be a direct consequence of driver drowsiness [3], and can lead to fatal road accidents. Moreover, mental fatigue can result in unsafe practices and poor performance in occupations requiring prolonged operator attention e.g. for crane operators [4]. Mental fatigue and drowsiness can be measured in different ways such as using psychometric questionnaires [5] or vigilance tests like the Psycho-motor Vigilance Test [6]. A major drawback of these methods is that they are intrusive on the attention of an operator and hence cannot be used in real time to measure the drowsiness of a driver. Therefore, other passive sensing techniques are generally preferred for measuring drowsiness, including measuring heart rate [7], increases or decreases in pupil size [8], and changes in eye blink rate [9]. Among the available passive methods, EEG can measure neurophysiological function, and hence may be a more reliable method to obtain measures of fatigue, and importantly, the moment-to-moment variations that correlate with reaction times to road events. The correlation between mental fatigue and EEG spectral features has been established in different studies [10][11][12].

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In this paper, we use a publicly available dataset [13] that contains EEG data from 27 subjects recorded while they completed driving sessions in a 4-lane simulated environment. We extend the idea of measuring driver reaction time, to detecting ahead of time the reaction time of drivers to events on the road. We train a number of subject-independent models on frequency-power features extracted from the EEG data from a 2-second period before the road event, and evaluate each model using an independent subject's EEG data. Consequently, training and testing are done on separate subjects in order to mimic a more real world scenario where training data may not be available for an individual subject. We show that our models are able to predict both individual trial-level response times and the average reaction time for subjects.

II. LITERATURE REVIEW

To date, a number of studies have investigated using EEG measures for tasks such as classification of mental states [14][15] and detecting mental fatigue of drivers [16][17].

The EEG frequency bands that are noted in the literature that coincide with mental state activities are the alpha and theta bands. In a previous study [18], it was shown that in high attentional demand scenarios, an increase in theta power along with a decrease in alpha power is observed. In another study [19], it was found that an increase in lower alpha was observed when subjects were asked to remain awake while they were sleepy. When subjects were allowed to sleep a decrease in alpha and increase in theta power was observed. This study noted that the alpha band was the most pertinent band for studying mental state. In another study where the EEG of industrial workers was investigated [20], it was found that an increase in alpha power was noticed a few minutes before sleep, while theta activity increased during sleep.

In [17] three classification strategies for mental fatigue recognition were evaluated: logistic regression, a transfer learning-enabled classifier, and a deep-learning based classifier called EEGNet. The results show that the transfer learning-enabled classifier outperformed other approaches by a significant margin.

Many reaction time prediction studies to date have used EEG data in a subject-dependent manner, where data for a subject is included as part of the model training process. This may not be practical for real world drowsiness monitoring systems however, as a reaction time prediction model would need to be trained on a per-subject basis. An example of this is seen in the work reported in [16] where inter-subject transfer based learning was used to detect mental fatigue.

In their study, they also explored model training using one channel of EEG compared to multiple channels. A Random forest was used to select one channel, and this gave better accuracy for classification. The model achieved an accuracy of 73.01% and 68% with Maximum Independent Domain Adoptation (MIDA) for all channels and Transfer Component Analysis (TCA) for one channel in the occipital region, respectively.

There has also been research conducted on measuring driver reaction time in non-computer simulated driving environments. In one particular study, the authors explored the relationship between TTC (time to collision) and the reaction time of the driver [21]. A real world driving task experiment was conducted where mock pedestrians were intermittently introduced on the road. Differences in the reaction times of the drivers for braking, steering the vehicle, and operating the accelerator pedal were studied. This study confirmed that there was a linear relationship between a driver's reaction time and TTC. TTC is calculated as S/V where S indicates vehicle distance from pedestrians and V stands for speed of the vehicle. Also, it was found that drivers have a faster reaction time when pedestrians come from the right hand side of the road. The average reaction time for accelerator pedal operation was 0.6 sec for small TTCs and 3 sec for long TTC. The reaction time range for braking was 0.65 to 1.6 sec, and for steering ranged from 0.4 to 1.6 sec.

In [15] the authors explored whether dry frontal electrodes could be used to predict the reaction time of a driver, and note that using multi channel electrodes may not be suitable for real time applications. Their study filtered EEG bands into four frequency bands with a 2 min window centered on the event onset. Their result showed that there was a positive correlation with delta band power and a negative correlation with other band powers.

In summary, alpha and theta bands are shown to be the most pertinent bands for predicting mental fatigue in drivers. There have been a few works to date that have focused on predicting the reaction times of drivers to road events using EEG measures, hence we explored the utility of alpha and theta band power measures for this purpose.

III. Methods

A. Dataset

A publicly available dataset is used in this paper, and is comprised of 32-channels of Electroencephalography (EEG) data for 27 subjects driving a vehicle in a simulated environment on a four-lane highway [13]. The dataset was collected with approval from the Institutional Review Board of the Veterans General Hospital, Taipei, Taiwan. Data collection was performed in strict accordance with the recommendations in the Guide for the Committee of Laboratory Care and Use of the National Chiao Tung University, Taiwan. EEG signals were captured using a Scan SynAmps2 Express system (Compumedics Ltd., VIC, Australia) using Ag/AgCl electrodes with mastoid references and a 500 Hz sampling rate. The Automatic Artifact Removal (AAR) plug-in for EEGLAB was used for data cleaning and correction of common artefacts. EEG was converted to a common average reference. Multiple sessions were captured for some subjects. To avoid issues with information leakage we combine separate session dataset on a per-subject basis. We discarded datasets for 3 subjects due to anomalous EEG data. In the experiment, the subjects were instructed to keep driving in the middle of a highway. Events were induced to deviate the vehicle left and right (drift) at random intervals. Each random deviation event subsequently had a deviation onset, a response onset and response offset. The response onset and offset indicate when the driver initiated their corrective driving response to the lane deviation and when it was completed, respectively.

Figure 1 illustrates the behavior of a driver in the simulated environment. In a 90-min driving task, the road-deviation events are randomly distributed.

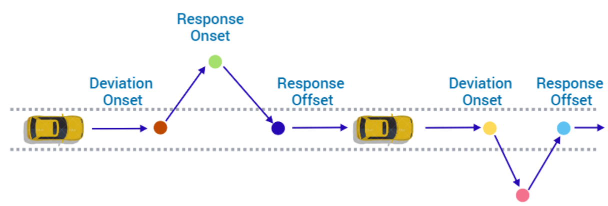

Fig. 1: Illustration of captured driving behaviours in an immersive driving simulator

B. Feature Extraction

We extracted 2-second EEG epochs across all EEG channels that directly preceded each road event (deviation onset), and computed Power Spectral Density (PSD) features using Welch's method [22]. PSDs are computed for delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-12 Hz) and beta (14-20 Hz) bands. The reaction time for each road event (trial) is computed as the deviation offset minus the deviation onset. Since we were interested in predicting the subject's reaction time before the event, we extracted a 2-second EEG epoch before the deviation onset. We explored different epoch lengths that preceded the deviation events, and found 2-second epochs to be optimal.

C. Subject-independent Analysis / Machine Learning

Our analysis was subject-independent which means that the training and testing data sets were kept independent. We used a leave-one-subject-out validation approach, hence for each of the 24 subject's trials, we trained a model on the other 23 subjects and benchmarked this trained model on that subject's independent data i.e. we trained the same number of machine learning models as the subjects. Mean Absolute Error (MAE) was used to asses performance i.e. how well we can predict reaction time (deviation offset - deviation onset) for the road events. We employed a number of classical machine learning approaches [23], specifically we used Bayesian Ridge Regression and Artificial Neural Networks (ANN). We used the default parameters for the

Bayesian Ridge algorithm. For ANN, we used the following hyperparameters: the activation function used was ReLU, we kept the maximum number of iterations to 300, the learning rate was set at 0.001, and we selected Nesterov momentum.

D. Results and Baseline Comparison

We used a dummy regressor as a baseline for each subject, that calculates MAE using the average of the reaction times of the independent subjects. As can be seen from Table I, in all of the four frequency bands, both of the machine learning approaches have performed better than the dummy regressor. Only in the case of beta PSD features, Bayesian Ridge had an almost a similar performance to that of the ANN approach.

TABLE I: Aggregate Mean Absolute Errors Across Subjects

Bands	Bayesian Ridge	ANN	Dummy
Alpha	0.53 (std: 0.25)	0.51 (std: 0.23)	0.58 (std: 0.27)
Theta	0.55 (std: 0.32)	0.54 (std: 0.29)	0.58 (std: 0.27)
Beta	0.58 (std: 0.26)	0.59 (std: 0.26)	0.58 (std: 0.27)
Delta	0.57 (std: 0.27)	0.54 (std: 0.26)	0.58 (std: 0.27)

In Figure 2 we show box plots illustrating the performance of PSD features used in conjunction with our ML approaches for alpha, theta, delta and beta frequency bands compared to a dummy classifier across subjects. Notably, the median value of MAE for each band is lower than that of the dummy. In particular, we are interested in MAEs for alpha and theta since these two bands are typically associated with attention-related mental activity [18] [20] [19]. As eye movement artefacts had already been removed from the data, unsurprisingly the results for delta are comparatively worse than alpha and theta band features. In the box plot, we have plotted only the best results for each band which means that three of the results are from ANN regression, and one from Bayesian Ridge Regression.

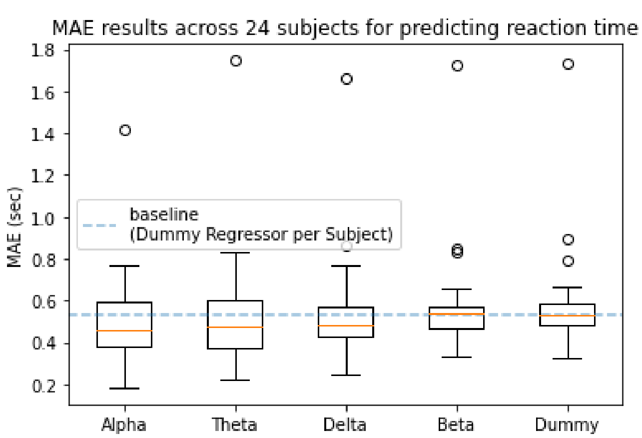

Fig. 2: Comparison of MAEs for different frequency bands

In Table II we show the per-subject MAE results for alpha and theta band features when used to predict reaction time using the ANN regressor. Columns 'N' and 'RT' show the number of events (for each subject) and the averaged reaction time for each subject, respectively. We additionally included Pearson-r correlation coefficients for predicted vs ground truth reaction times for each subject, as a trained model may have correctly predicted the trial-to-trial variation in reaction times, but may have consistently overestimated or underestimated these (by some offset or multiplier). Instances exist where a model has predicted a subject's average reaction better than the dummy regressor, yet has failed to capture the trial-to-trial variations in reaction times, indicated by a low correlation coefficient, and relatively lower MAE compared to the dummy MAE. We have indicated instances where the two-tailed p-value for the correlation coefficient is below .05 with an asterisk, and used two asterisks where it is below .01. As can be seen, for the majority of subjects, successful predictions for driver reaction time can be made on a per-subject per-trial basis i.e. significantly above chance.

TABLE II: Subject-independent Prediction Results

Sub	N	alpha corr	alpha MAE	theta corr	theta MAE	RT	dummy MAE
1	780	0.04	0.45	0.05	0.49	1.24	0.38
2	673	0.12**	0.31	0.10**	0.36	0.78	0.49
3	356	0.40**	0.77	0.29**	0.83	1.53	0.89
4	1356	0.33**	0.64	0.18**	0.68	1.15	0.55
5	355	0.34**	0.48	0.31**	0.43	1.13	0.43
6	617	0.06	0.48	0.07	0.53	1.03	0.51
7	414	0.28**	0.40	0.22**	0.37	0.78	0.59
8	499	0.25**	1.40	0.17**	1.74	2.57	1.73
9	737	0.12**	0.47	0.18**	0.55	0.69	0.60
10	727	0.07*	0.36	0.04	0.22	0.58	0.60
11	1412	0.09**	0.67	0.08**	0.70	1.43	0.67
12	434	0.31**	0.30	0.31**	0.32	1.07	0.32
13	1173	0.11**	0.42	0.12**	0.52	1.40	0.42
14	983	0.20**	0.42	0.27**	0.45	1.00	0.49
15	2031	0.07	0.58	0.37**	0.54	1.30	0.53
16	748	0.29**	0.76	0.35**	0.80	1.86	0.79
17	2234	0.13**	0.58	0.04*	0.69	1.09	0.56
18	330	0.18*	0.36	0.38**	0.35	0.89	0.55
19	1007	0.25**	0.38	0.27**	0.37	0.88	0.49
20	669	0.36**	0.41	0.38**	0.40	1.09	0.40
21	205	0.54**	0.28	0.58**	0.26	0.91	0.50
22	1094	0.16**	0.55	0.06	0.57	1.28	0.56
23	164	0.06	0.63	0.40**	0.45	1.41	0.53
24	637	0.04	0.18	0.02*	0.29	0.71	0.46

In Figure 3 we show the significant correlative relationship between the averaged predicted reaction time per subject and the averaged ground truth reaction time per subject. There is a significant correlation (Pearson-r: p=0.00008, r=0.71, N=24) indicating that it is also possible to predict the average reaction time of a subject i.e. whether they are a fast or slow responder in terms of reaction time.

Our results are consistent with existing EEG literature. As can be seen from the results in Table 1, using alpha and theta band features gives a lower error compared to the other bands, namely beta and delta i.e. alpha and theta band features were predictive of the ground truth reaction times.

IV. CONCLUSIONS AND FUTURE WORK

In this paper, we have investigated whether regression methods can be used to predict driver reaction time to

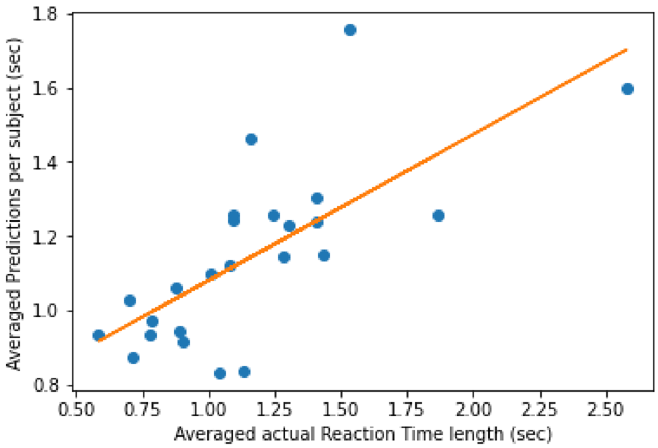

Fig. 3: Relationship between ground truth and predicted reaction times

deviations using EEG PSD features that precede the onset of the deviation events. We were able to achieve good results using simple machine learning approaches that use alpha and theta band features from human EEG. Moreover, using the same methods and averaging predictions we have shown it is possible to predict whether a subject is a slow or fast responder to events on the road. The training and testing approach in our analysis keeps each subject's testing data separate from the training of models by using a leave-one-subject-out validation approach i.e. we use subject-independent models. Our contribution in this paper is novel in that we shown it is possible to use subject-independent models with EEG features from time periods that preceded the onset of simulated deviation events, to successfully predict a person's reaction times to those events.

Our future work will focus on channel selection, combining different frequency bands, and placing an increased emphasis on using deep learning approaches to further maximize performance. Similarly, we will explore the temporal aspects of reaction times throughout the driving sessions as currently we are doing prediction for single events.

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