Detection of Anticipatory Brain Potentials during Car Driving

Zahra Khaliliardali, Ricardo Chavarriaga, Lucian Andrei Gheorghe, and José del R. Millán

***Abstract*— Recognition of driver's intention from electroencephalogram (EEG) can be helpful in developing an in-car brain computer interface (BCI) systems for intelligent cars. This could be beneficial in enhancing the quality of interaction between the driver and the car to provide the response of the intelligent cars in line with driver's intention. We proposed investigating anticipation as the cognitive state leading to specific actions during car driving. An experimental protocol is designed for recording EEG from 6 subjects while driving the virtual reality driving simulator. The experimental protocol is a variant of the contingent negative variation (CNV) paradigm with *Go* and *No-go* conditions in driving framework. The results presented in this study support the presence of the slow cortical anticipatory potentials in EEG grand averages and also confirm the discriminability of these potentials in offline single trial classification with the average of 0.76 ± 0.12 in area under the curve (AUC).**

I. INTRODUCTION

Assessing correlates of cognitive states and detecting the subject's intention can help in enhancing the quality of BCI systems [1]. This could be beneficial for developing an in-car BCI system that monitor the driver's brain state during driving intelligent cars. The main idea of BCIs for intelligent cars is based on the concept of shared control (SC) [2], in which the control over the system is shared between the driver and the car. Deploying such a system can improve the interaction through aligning the response of the intelligent car with the intention of the driver. For instance, considering a junction with a traffic light in red color where an unattentive driver has no intention to brake, the intelligent car assistance could safely stop the car without surprising him with an emergency brake at the last second.

Previous studies of monitoring driver's brain state have mainly focused on the level of driver's drowsiness/arousal using electroencephalogram (EEG) and electrooculogram (EOG) [3], [4]. EEG-based systems also investigated the detection the mental workload of drivers [4]. Recently Haufe et al. investigated the detection of the emergency braking before the action onset. The results of this study indicate that the driver's intention to perform emergency braking can be detected 130ms earlier than the car pedal responses using EEG and electromyography (EMG) [5].

We are interested in anticipation related signals during driving. Anticipation is a cognitive process during which a person actively engages in a preparatory phase required for the stimulus perception and execution of the specific actions after the appearance of specific stimulus [6]; i.e. the appearance of a red light signal when a traffic signal turns from green to yellow. In simple psychophysical paradigms, a central negativity has been observed in the scalp EEG during the interval between the predictive and contingent stimuli. This signal, which typically lasts from about 300 ms to several seconds with magnitudes up to 50μV has been termed *contingent negative variation* (CNV) potential [6].This potential has been linked to the preparatory processing required for appropriate actions at the arrival of future events [7], [8]. Nevertheless, apart from few examples [9], [10], [12], these potentials have been studied using simple procols and stimlui.

In this work, we recorded EEG, EOG and EMG signals from 6 subjects using a variation of the classical CNV paradigm in a simulated driving experiment. We report anticipatory brain signals and evaluate the discriminability of these potentials using single trial classification methods. In the following section, we present the experimental set-up and data acquisition. In Section III, we present the results of offline single trial recognition of anticipation. Finally, in Section IV, we discuss the current results and suggest some future directions.

II. METHODS

A. Experimental protocol and set-up

Six healthy right-handed Subjects (24-32 years, 1 female) participated in this study, all had normal or corrected to normal vision. Subjects sat comfortably in the driver's chair of a car simulator in front of a projector

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Fig. 1: Experimental setup. The subject is seated in the car simulator with the EEG, EOG, and EMG electrodes. *Inset*: Illustration of the visual stimuli corresponding to the virtual roadway environment

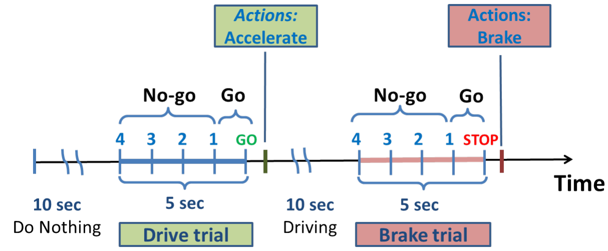

Fig. 2: Timeline of protocol, start with waiting 10 seconds for the first round of count down numbers followed by 'Go' cue to start, continue driving for around 10 second and the second round of count down followed by 'Stop' cue, waiting for 10 second after stopping the car and so on. Two types of trials: Brake and Drive and each trial contains one *Go* epoch and three *No-go* epochs.

screen, which shows a virtual roadway environment. The task is to drive a virtual car along a highway (including soft turns) using the steering wheel and gas/brake pedals (See Figure 1). At specific moments during driving, cued by visual stimulus,drivers will be asked to brake or to resume their journey.

In order to involve subjects in anticipating for upcoming future events (such as the color changes of traffic light in real driving), we have designed a protocol where one or more contingent warning stimuli predict the imperative stimulus (Figure 2). A count down appears at the centre of the screen from '4' to '1' followed by a 'Go' cue. Subjects are instructed to push the gas pedal immediately and briskly after the appearance of the 'Go' cue. They have to continue driving at a speed of 100 km/h. Fifteen seconds ($\pm$2.87) after, a new series of count down stimuli appear followed by a 'Stop' cue. Immediately after this cue, subjects are supposed to push the brake pedal briskly. A new count down followed by 'Go' cue will appear again after 15($\pm$2.87) seconds and so on. In this experiment, the interval between the onset of each cue (e.g. '1') to the next one (e.g. 'Go') is one second. Note that the count down stimuli allows the subjects to anticipate the moment where they should brake, as opposed to the emergency braking tested by Haufe and colleagues [5].

As can be seen in Figure 2, There are two types of trials in our experiment: Drive and Brake trials. The former comprises the time interval between the appearance of the numbers and the 'Go' cue, while the latter comprises the time interval between the numbers and the 'Stop'. In both cases, each trial contains three *No-go* epochs and one *Go* epoch, in the terms of the classical *Go* and *No-go* definition. The *No-go* epoch is the time interval between the appearance of one number to the next one, in when the subjects are not supposed to do any action. The time interval between '1' cue and the 'Go/Stop' cue, which subjects are supposed to perform an action, corresponds to a *Go* epoch. Each session of the experiment consists of four runs. Each run is around 15 minutes and contains an average of 84 ± 15.29 trials (for each type of Drive and Brake trials)

B. Data acquisition and preprocessing

EEG, EOG, and EMG signals were acquired with a portable system (Bio-semi Active Two). 64 EEG Ag-AgCl electrodes placed according to international extended 10-20 standard. Three flat active electrodes were used to record EOG, placed above the nasion and below the outer canthi of the eyes. The EMG signal was recorded using one set of bipolar electrodes placed on the subject's right leg (on the *tibialis anterior*) muscle. The sampling rate of entire synchronous recording was 2048 Hz. To reduce artifacts, the subjects are instructed to fixate on a point on the center of screen and to minimize facial or head movements during the appearance of the stimuli.

Event markers such as the triggers of the pedals and steering, and the position of the car were provided by the car simulator at a sampling rate of 256 Hz. Physiological signals (i.e. EEG, EMG, and EOG) were down-sampled to 256 Hz and synchronized with the data from the car simulator.

EEG was preprocessed using common average reference (CAR) [11] and then filtered by using band-pass Butterworth filter between 0.1 to 1 Hz, due to the frequency range of CNV potentials [12]. EMG signals were filtered with a bandpass Butterworth filter in the range of 20 to 50 Hz and smoothed with a moving average filter (time window = 25 samples). EEG ad EMG signals were segmented into *Go*, *No-go* epochs for both Drive and Brake trials. Moreover, for each epoch (*Go* and *No-go*), the data is baseline corrected using the sample at the cue onset. The onset of the appearance of 'Go/Stop' cue on the screen is defined as 0s. In this study, we didn't focus on EOG signals.

C. Feature extraction and classification

We evaluate the possibility of differentiating between *Go* and *No-go* epochs on a single-trial basis. For that, we used a classification approach due to the high trial to trial variability of the CNV brain potentials. Separate classifiers were built for Drive and Brake trials. In each case, we compare two classification methods: linear and quadratic discriminant analysis (LDA and QDA, respectively) [13]. Classification performance was assessed using 4-fold cross-validation, where each fold corresponds to a separate run.

For each epoch, the Cz potentials at four equally spaced time points (i.e., at -0.2s, -0.4s, -0.6s, -0.8s) are used as a feature vector. This number of features have been reported to sufficiently represent the evolution of the CNV potentials in a 1s window [12].

The performance of the single trial classification is evaluated using the area under the curve (AUC) in the receiver operating characteristics (ROC) space. AUC is an estimate of the probability that a classifier yield a higher rank to a randomly chosen target (i.e. *Go* epochs) than a randomly chosen non-target (*No-go* epochs) [14].

III. RESULTS

A. Event-related potentials

EEG grand averages are computed over all the Drive and Brake trials separately. Figure 3-a shows the EEG-grand average for Cz electrode for one subject. In both types of trials, we see a negative deflection starting about one second before the appearance of 'Go/Stop' sign; i.e. around the onset of the '1' on the screen, and it peaks at 0s which is the time of the appearance of 'Go/Stop' on the screen and back to zero after around 250ms later. This is consistent with the CNV potential reported in previous studies [6], [9], [12]. In addition, a clear difference can be observed between *Go* and *No-go* epochs (increasing negativity for *Go* and almost flat or slightly positive response for all the other *No-go* epochs). The topographic plots of average scalp distribution at different time points show that this negativity is maximal at Cz electrode. The same phenomenon has been observed for all subjects. Figure 3-b shows the grand averages of the EMG envelopes. The onset of increasing activity in EMG grand averages is around

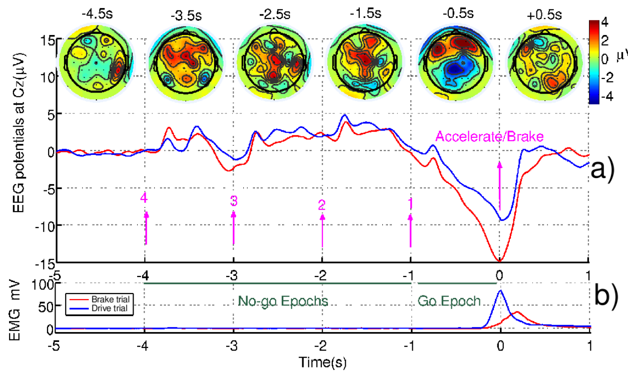

Fig. 3: a) Topographic representation of average EEG scalp distribution at different time points: 0.5 second before the onset of each cue which is shown by magenta arrow (top), Grand averages of for the Cz electrode is shown in blue for Drive trials and red in Brake trials (bottom). t=0 is the onset of the appearance of 'Go/Stop' cue and t=-4 is the onset of the appearance of the first count down cue. b) EMG grand averages to show the action execution (Drive trials:blue and Brake trials: red). This figure is plotted using the recording of subject-2, the same phenomena have been observed for all subjects.

-0.2s, confirming that there is no muscular activity on the leg during the preparation phase.

B. Single trial classification

The results of offline single trial classification using two different classifiers (LDA and QDA) are summarized in Table I. The classification results show relatively good sensitivity (with a mean value above 0.66; portion of GO trial that are classified as GO) and high specificity (with a mean value above 0.75; portion of NO-go trials that are rejected to be GO trials), irrespective of the classification method and type of trials. QDA classifiers performed slightly better than LDA for both Drive and Brake trials.

Independently of the classifiers, the classification performance was higher for Brake trials than for Drive trials. Noticeably, a higher negative peak was observed for Brake trial in EEG grand averages (see Figure 3). This difference can be due to the type of movements required for each type of trial. Indeed, in the Drive trials, subjects were supposed to push sharply the acceleration pedal, while for the Brake pedal they need to switch the pedal including releasing the acceleration pedal and pushing brake pedal sharply and immediately.

IV. CONCLUSIONS AND FUTURE WORKS

We investigate anticipation-related EEG signals during simulated car driving. Experiments with 6 subjects, show event-related potentials consistent with CNV signals reported in the literature [7], [8], [12]. Detection

TABLE I: Performance of classification (AUC-Sensitivity-Specificity)

	AUC				Sensitivity				Specificity			
Classifier	LDA		QDA		LDA		QDA		LDA		QDA	
Subject	Drive	Brake	Drive	Brake	Drive	Brake	Drive	Brake	Drive	Brake	Drive	Brake
1	0.86	0.91	0.89	0.92	0.75	0.84	0.75	0.84	0.84	0.86	0.87	0.88
2	0.87	0.96	0.87	0.96	0.82	0.96	0.82	0.92	0.83	0.88	0.86	0.72
3	0.71	0.76	0.73	0.78	0.59	0.68	0.44	0.68	0.73	0.74	0.88	0.75
4	0.56	0.65	0.65	0.67	0.48	0.62	0.50	0.55	0.62	0.63	0.74	0.78
5	0.72	0.83	0.69	0.82	0.67	0.71	0.54	0.74	0.72	0.7	0.27	0.23
6	0.50	0.72	0.52	0.73	0.44	0.58	0.53	0.57	0.63	0.74	0.57	0.82
Mean	**0.70**	**0.80**	**0.72**	**0.81**	**0.62**	**0.73**	**0.59**	**0.71**	**0.72**	**0.76**	**0.77**	**0.78**
SD	0.13	0.10	0.12	0.10	0.13	0.13	0.13	0.14	0.08	0.08	0.11	0.05

of this anticipatory brain potential can be useful for assessing the subject's intention before the execution of the planned action. Offline results using QDA and LDA classifiers show the feasibility of recognizing these signals in single-trial. This information can be exploited by in-car BCI systems that monitor the driver's brain state.

The results presented in the current work are promising since previous studies of anticipation-related potentials use simpler experimental setups and stimuli [6], [7]. In contrast, in our realistic driving experiment, EEG signals may be affected by visual distractors in the roadway and limb movements of subjects while driving. Despite this, we achieved high performance for discriminability of *Go* and *No-go* epochs.

Further analysis will be performed to test the specificity of our classifiers including the intervals while the subject was driving or waiting for the cues to start again (see Figure 2). Furthermore, artifact removal techniques will be implemented to reduce their effects on the EEG signal, and evaluate whether they lead to improved classification performance.

Although these results support the possibility of predicting the driver's intention through anticipatory brain potentials, the real-time applicability of the methods presented here raise new challenges. Particularly, the requirement of low frequency band pass filters designed for improving signal to noise ratio of slow CNV potentials, which may introduce significant delays. A better compromise on these delays and accuracy recognition rates will be explored in future.

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REFERENCES

[1] J. d. R. Millán, P. W. Ferrez, F. Galán, E. Lew, and R. Chavarriaga, "Non-invasive brain-machine interaction," *Int J Pattern Recognition and Artificial Intelligence*, vol. 22, pp. 959–972, 2008.

[2] F. O. Flemisch, C. A. Adams, S. R. Conway, K. H. Goodrich, M. T. Palmer, and P. C. Schutte, "The H-metaphor as a guideline for vehicle automation and interaction," *NASA Technical Memorandum 212672*, no. December, 2003.

[3] C. H. Chuang, P. C. Lai, L. W. Ko, B. C. Kuo, and C. T. Lin, "Driver's cognitive state classification toward brain computer interface via using a generalized and supervised technology," in *IJCNN*, 2010, pp. 1–7.

[4] F. C. Lin, L. W. Ko, S. Chen, C. Chen, and C. Lin, "EEG-based cognitive state monitoring and predition by using the self-constructing neural fuzzy system," in *ISCAS*, 2010, pp. 2287–2290.

[5] S. Haufe, M. S. Treder, M. F. Gugler, M. Sagebaum, G. Curio, and B. Blankertz, "EEG potentials predict upcoming emergency brakings during simulated driving," *Journal of Neural Engineering*, vol. 8, no. 5, pp. 1–11, 2011.

[6] W. G. Walter, R. Cooper, V. J. Aldridge, and W. C. Mccallum, "Contingent negative variation : An electric sign of sensorimotor association and expectancy in the human brain," *Nature*, pp. 380–384, 1964.

[7] W. Kirsch and E. Hennighausen, "ERP correlates of linear hand movements: Distance dependent changes." *Clin Neurophysiol*, vol. 121, pp. 1285–1292, 2010.

[8] P. Kropp, A. Kiewitt, H. Gbel, P. Vetter, and W. Gerber, "Reliability and stability of contingent negative variation." *Appl Psychophysiol Biofeedback*, vol. 25, no. 1, pp. 33–41, 2000.

[9] J. D. Bayliss, "A flexible brain-computer interface," Ph.D. dissertation, University of Rochester, 2001.

[10] R. Chavarriaga, X. Perrin, R. Siegwart, and J. d. R. Millán, "Anticipation- and error-related EEG signals during realistic human-machine interaction: A study on visual and tactile feedback," *34th International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC12)*, 2012.

[11] D. McFarland, L. McCane, S. David, and J. Wolpaw, "Spatial filter selection for EEG-based communication," *Electroencephalography and Clinical Neurophysiology*, vol. 103, no. 3, pp. 386–394, Sep. 1997.

[12] G. Garipelli, R. Chavarriaga, and J. d. R. Millán, "Single trial recognition of anticipatory slow cortical potentials:the role of spatio-spectral filtering," *5th International IEEE/EMBS Conference on Neural Engineering (NER)*, pp. 408–411, 2011.

[13] R. O. Duda, P. E. Hart, and D. G. Stork, *Pattern Classification*, 2nd ed. New York: Wiley, 2001.

[14] T. Fawcett, "An introduction to ROC analysis," *Pattern Recognition Letters 27*, pp. 861–874, 2006.