Final version: Journal of Neural Engineering, vol. 12: p. 066006, 2015
doi: 10.1088/1741-2560/12/6/066006

Action Prediction Based on Anticipatory Brain Potentials during Simulated Driving

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

* Defitech Chair in Brain-Machine Interface, Center for Neuroprosthetics, Institute of Bioengineering and School of Engineering, École Polytechnique Fédérale de Lausanne (EPFL), Campus Biotech H4, 1202, Geneva, Switzerland.
** Nissan Motor Co., Ltd. Research Division, Research Planning Department, Atsugi, Japan.

E-mail: `zahra.khaliliardali@epfl.ch`

Abstract

Objective. The ability of an automobile to infer the driver's upcoming actions directly from neural signals could enrich the interaction of the car with its driver. Intelligent vehicles fitted with an on-board brain-computer interface (BCI) able to decode the driver's intentions can use this information to improve the driving experience. In this study we investigate the neural signatures of anticipation of specific actions, namely braking and accelerating. *Approach.* We investigated anticipatory slow cortical potentials (SCPs) in electroencephalogram (EEG) recorded from 18 healthy participants in a driving simulator using a variant of the contingent negative variation (CNV) paradigm with *Go* and *No-go* conditions: count-down numbers followed by 'Start'/'Stop' cue. We report decoding performance before the action onset using a quadratic discriminant analysis (QDA) classifier based on temporal features. *Main Results.* (i) Despite the visual and driving related cognitive distractions, we show the presence of anticipatory event related potentials locked to the stimuli onset similar to the widely reported CNV signal (with an average peak value of -8 μV at electrode Cz). (ii) We demonstrate the discrimination between cases requiring to perform an action upon imperative subsequent stimulus (*Go* condition, e.g. a 'Red' traffic light) versus events that do not require such action (*No-go* condition; e.g. a 'Yellow' light); with an average single trial classification performance of 0.83±0.13 for braking and 0.79±0.12 for accelerating (area under the curve). (iii) We show that the centro-medial anticipatory potentials are observed as early as 320±200 ms before the action with a detection rate of 0.77±0.12 in offline analysis. *Significance.* We show for the first time the feasibility of predicting the driver's intention through decoding anticipatory related potentials during simulated car driving with high recognition rates.

Keywords: BCI; Anticipation ; EEG; CNV; Intention detection; Car simulator; SCP.

1. Introduction

Car drivers are constantly involved in anticipatory and preparatory tasks prompted by processes that can be either internal (endogenous) or triggered by cues from the environment (exogenous). Brain-computer interface (BCI) systems can potentially be used to recognize the driver's intention for a movement such as pressing pedals, or turning left or right before any overt action is performed. Predicting the driver's will can help the driving assistance system of an intelligent car to provide support that is not only in-line with the situations on the road (based on the in-car sensors), but also and more importantly, aligned with the driver's intention (mediated by the driver's BCI). This will ensure a seamless interaction between the car and the driver.

To date, studies on monitoring the driver's brain state have mainly focused on the driver's drowsiness/arousal using a combination of Electroencephalogram (EEG) and electrooculogram (EOG) signals [1, 2]. EEG-based systems have been also employed for the detection of driver's workload [2, 3]. Haufe et al. [4] explored the detection of emergency braking before the action onset using EEG and electromyography (EMG). The results of this offline study indicate that the driver's intention to perform emergency braking can be detected as early as 130 ms before the car pedal responses . More recently, they assessed the applicability of their system in real-world driving [5] replicating the findings obtained with the car simulator [4]. Kim et al. [6] have extended these findings in different simulated driving situations, and were also capable to different emergency braking from normal braking.

In this work, we investigate the prediction of driver's action based on the decoding of anticipatory brain potentials. Anticipation generates an endogenous pre-activation of underlying neural structures, during which a person actively engages in a preparatory phase after a warning stimulus, in order to execute a specific action after a relevant imperative stimulus [7]. An example in the driving scenario is the color changes of a traffic light, when the traffic light is turning from 'Green' to 'Yellow' to 'Red'. In this case, 'Yellow' is the warning stimulus, as it does not require any mandatory action and simply predicts the appearance of the imperative stimulus 'Red', upon whose appearance the subject is supposed to brake immediately. Therefore, we evaluate the feasibility of predicting the movement onset (e.g. pressing the brake pedal) through anticipatory brain potentials. This will be beneficial in scenarios where the driver is engaged by external events for which he/she needs to perform an immediate action (e.g. 'Red' light) in contrast to occasions where there is no need for an immediate response (e.g. 'Yellow' light).

As an example of how a BCI based on anticipatory brain potentials can enhance driving, consider a junction with a traffic light turning 'Red'. Two cases might happen. (i) For an inattentive driver who is not aware of the need to brake, the BCI does not detect the presence of anticipation-related potential. Then, the driving assistance generates a warning feedback to the driver while it also initiates the braking action smoothly, so that the driver has the time to become aware of the situation and finish braking the car by him/herself. This kind of driving assistance would prevent an automatic emergency braking at the last moment, which may result in a negative surprise and unpleasant experience for the driver who could feel under the control of the smart car rather than controlling it. (ii) If the driver is aware of the turning traffic light and has the intention to brake, the BCI detects the presence of a CNV and an automatic braking is unnecessary. Still, further driving assistance could be also provided by facilitating the driver's intended action (i.e. initiating the braking action smoothly). We believe that a smart car endowed with a such BCI will lead to a more pleasant and seamless interaction between the two as its driving assistance will always be in accord with the driver's intention. It is worth noting that, the real-time information about the presence and status of a traffic lights can be detected by the embedded sensors in the car [8, 9] which could be transferred to the proposed BCI system. Furthermore, the advent of autonomous cars is accelerating the use of communication networks among cars and key traffic elements, such as traffic lights, that will provide an intelligent car with the necessary information about the status of traffic and other vehicles on the road.

In the standard paradigms for studying anticipatory processes, a first warning stimulus (S1) predicts the appearance of second imperative stimulus (S2), signaling that the user has to perform a specific action. A central negative deflection has been observed in the scalp EEG during the interval between the warning (S1) and imperative stimuli (S2) [7]. This signal, termed Contingent negative variation (CNV) potential, develops during most of the inter-stimulus interval and can last from about 300 ms to several seconds with magnitudes up to 50 μV. Generally, the negativity ends sharply with the onset of Go cue. This potential is linked to the preparatory processing required for appropriate actions at the arrival of future events [7, 10, 11]. Interestingly, recent studies have shown the possibility of detecting similar potentials in complex experimental set-ups that involve a simulated tele-presence robot [12] or operation of Internet browsers [13].

Recently, Garipelli et al. [13] studied offline the anticipation-related brain signals and highlighted the advantages of using weighted average spatial smoothing filters and removal of the infra-slow oscillations (below 0.1 Hz). However, the single-trial analysis results of this study were confined only to synchronous classification. Similar preprocessing methods have been proposed for the detection of movement intention through slow Movement-related cortical potentials (MRCPs) or Readiness potentials (RPs) pointing to similar frequency ranges. Both CNVs and MRCPs result in a similar deflections in the slow brain potentials of EEG called Slow cortical potentials (SCPs). SCPs are changes in cortical polarization of the EEG lasting from 300 ms to several seconds before the movements. Negative polarization have received different labels, depending upon the experimental scenarios in which they were observed: MRCPs or RPs in preparation for voluntary movements, and CNV if it occurs between two consecutive stimuli or responses [14]. Niazi et al. [15] as well as Lew at al. [16] have exploited, in offline experiments, the RPs for the *prediction* of a forthcoming self-paced movement 66.6±121 ms and 167±68 ms before the action onset with an average maximum true positive rate (TPR) of 82.5±7.8 and 0.76±0.07, respectively. More recently, Xu et al. showed the online *detection* of MRCPs with a TPR up to 0.79 [17]. However, the peak of decoding performance is achieved about 300 ms after the movement onset, unlike our approach for the *prediction* of movement intention that works before the movement onset.

Following the main goal of this study, we recorded EEG signals from 18 healthy volunteers using a variation of the classical CNV paradigm in a simulated driving experiment. In this study, we address the following questions: (i) Is it possible to observe anticipatory related potentials during driving? Considering that, unlike controlled psycho-physical experiments: driving task involves multitasking (upper and lower limb movements) and the visual input is richer (including the moving stimuli and other distractions). (ii) If this is the case, can these potentials be recognized in single trials? (iii) We further investigate the possibility of detecting asynchronously the movement intention with a moving window. To the best of our knowledge, no study has been reported on the use of anticipatory brain potentials in order to detect movement intention. How early could these potentials be detected in real-time?

The experiments and proposed methods are detailed in Section 2. Section 3 presents the results of single-trial recognition of anticipation related potentials. Finally, we discuss the results in Section 4, and suggest future directions in Section 5.

2. Materials and Methods

2.1. Experimental protocol and set-up

Eighteen healthy, right-handed subjects (2 female, average age 25.5±4.1 yrs) participated in the experiment. All had normal or corrected-to-normal vision and all had an ample driving experience. The experimental protocols were approved by the local ethical committee and subjects provided informed consent. Subjects sat in a car simulator where a virtual roadway environment was displayed using the open source *VDrift* software on the screen (experimental setup can be seen in Figure 1.a). The participants were asked to drive the virtual car along a highway with soft turns, at a speed of 100 Km/h, using the steering wheel, accelerate/brake pedals. There was no other car on the virtual road. Visual cues were provided to the subjects at random times indicating them to stop or resume their journey. The virtual environment was shown on a projection screen for six of the subjects (see Figure 1.a: the size of the screen was 100 inch and placed approximately 1.5 meter from the subject's seat). For the remaining participants we used three 27 inch 3D monitors.

During the task one or more warning stimuli predicted the imperative stimulus (see Figure 1.b and c). This design allowed us to test the difference between predictable future events from the environment, some of them did not require the subjects to perform an action (*No-go*), and imperative ones (*Go*). At a random time point during driving, a visual cue appeared at the center of the screen showing a count-down from '4' to '1', in seconds, followed by a text cue 'Stop'. Upon this cue subjects were instructed to immediately push the brake pedal. After a given period, a similar count-down of 4 seconds appeared, but this time it was followed by a 'Start' cue. Upon the onset of this cue subjects had to push the acceleration pedal briskly. The interval between two count-downs was drawn from a uniform distribution in the range of [10 20] s (mean and standard deviation of 15 $\pm$ 2.87). In this paradigm, cues with numbers ('4', '3', '2', '1') corresponded to the warning stimuli, predicting the appearance of the imperative stimulus ('Start'/'Stop'). The size of stimulus (0.1 rad) in the driver's visual field was similar for both setups (i.e. using the projection screen and the 3D monitors).

As can be seen in Figure 1.c, we defined two types of trials in our experiment: *Drive* and *Brake* trials. The former comprises the time interval preceding the 'Start' cue, while the latter comprised the time interval before the 'Stop' cue. In both cases, each trial contained three *No-go* epochs and one *Go* epoch, in terms of the classical *Go* and *No-go* definition [7]. A *No-go* epoch is defined as the time interval between the appearance of one number in the count-down to the next one, in which subjects were not supposed to do any action after the cue. The time interval between cue '1' and the 'Start/Stop' cue, in which subjects were supposed to perform an action, is defined as a *Go* epoch.

Each subject performed one experimental session composed of four runs of 15 minutes, each with resting periods of 5-10 min in between. Each session contained an average of 91 $\pm$ 9.5 and 86 $\pm$ 9.5 trials for *Drive* and *Brake* trials, respectively. During the *Drive* trials the car was stopped, and during the *Brake* trials, the car was moving and subjects were continuously pressing the gas pedal fully. Therefore, the visual information flow was richer in the *Brake* trials than in the *Drive* trials. Moreover, the *Brake* trials required a different movement, switching from the gas pedal to the brake pedal, while for *Drive* trials the subject only had to press the gas pedal. To reduce EEG contamination due to movement artifacts , the subjects were instructed to fixate a cross (size is around 0.02 rad) on the center of the screen to minimize facial or eye movements during the appearance of the stimuli.

For 10 (out of 18) subjects we also provided their Reaction-time (RT) after the *Brake* trials as a behavioral feedback. We hypothesized this feedback can help subjects to better synchronize their actions (pressing the brake pedal) with the onset of the imperative cue ('Stop'). To summarize, we defined two sets of recordings, *Group1* and *Group2*. *Group1* included the recordings of subjects S1-S9, in which no feedback was provided to the subjects (S1-S6 with flat screen, S7-S9 with 3D screens). *Group2* contained the recordings of subjects S10-S18, where the subjects received RT feedback for the *Brake* trials (all subjects worked with 3D screens).

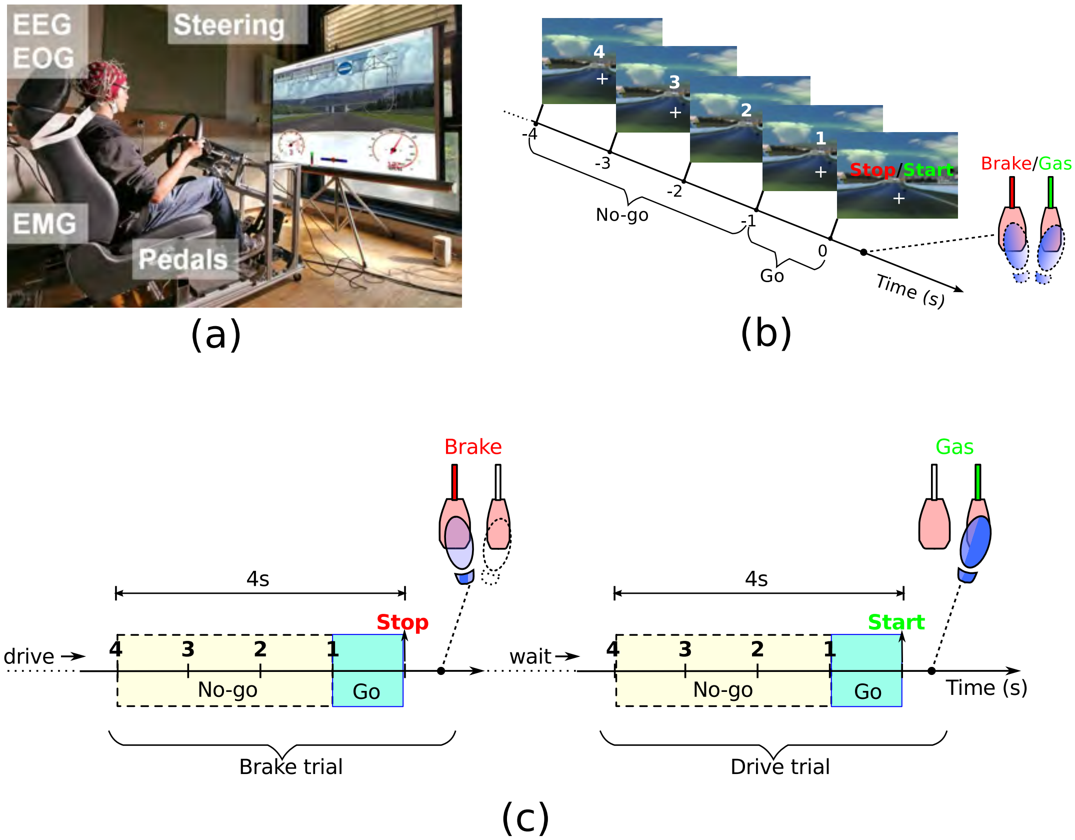

Figure 1. a) The experimental setup with the projection screen showing the virtual roadway environment and the car meters. b) Snapshots of the screen with the count-down stimuli. c) Time-line of the protocol: the first round of count-down stimuli followed by the 'Stop' cue to brake, waiting for around 15 seconds, and second round of count-down and 'Start' cue to accelerate. It corresponds to the two types of trials: *Brake* and *Drive* each containing one *Go* and three *No-go* epochs.

2.2. Data acquisition and preprocessing

The EEG was acquired using 64 electrodes arranged in the modified 10-20 international standard along with three EOG electrodes and two EMG electrodes using a Biosemi Inc ActiveTwo system. The EOG electrodes were placed above the nasion and below the outer canthi of the eyes, to derive horizontal, vertical and radial components. A pair of surface EMG electrodes were mounted on the *tibialis anterior* muscle of the subject's right leg.

Event markers such as the triggers of the pedals (accelerate/brake) and steering, as well as 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 acquired at a sampling frequency of 2048 Hz, then down-sampled offline to 256 Hz and synchronized with the car simulator data.

The EEG data were spatially filtered by a common average reference (CAR) [18]. Then, EEG was further filtered in the spatial domain using a weighted average filter (WAVG), as it has been shown to improve the classification performance of CNV potentials [13]. WAVG can be seen as the opposite of the Laplacian filter, where the average neighboring activity is added, rather than subtracted. Given the value of the i^{th} electrode, $e_i^{CAR}(t)$ after CAR, WAVG returns $e(t) = e_i^{CAR}(t) + \frac{1}{K}\sum_j^K e_j^{CAR}(t)$, where, K represents the number of nearest neighbor electrodes considered. Afterwards, EEG was spectrally filtered by means of a non-causal narrow band-pass IIR filter (4th order, Butterworth) with cutoff frequencies between 0.1–1 Hz. EMG signals were rectified and then filtered with a bandpass Butterworth filter in the range of 20 to 50 Hz and smoothed with a moving average filter (window of 25 samples) [16]. EEG and EMG signals were segmented into *Go*, and *No-go* epochs (see Figure 1.c). The onset of the appearance of 'Start/Stop' cue on the screen is defined as time 0 s. For each epoch (*Go* and *No-go*) the data were baseline corrected to the value of the sample at the onset of each cue.

2.3. Feature extraction and classification

2.3.1. Single trial classification

We evaluated the possibility of differentiating between *Go* and *No-go* epochs on a single-trial basis using well-known pattern recognition methods. We decoded activity at vortex (central-midline) where anticipation-related SCPs are most prominent [13]. For each epoch, the processed Cz potentials at 4 equally spaced time points (i.e. at -0.8 s, -0.6 s, -0.4 s, and -0.2 s) were used as a feature vector, $\mathbf{x} = [e_{Cz}(T_1)\, e_{Cz}(T_2)\, \ldots\, e_{Cz}(T_4)] \in R^4$ where, T_k represents k^{th} time point. The choice for the number and timing of the features was based on previous studies from our group [13, 19]. In order to investigate the possibility of early detection, the proposed feature vector includes information only until 0.2 s before the onset of the imperative stimulus 'Start'/'Stop'.

For classification, we use the quadratic discriminant analysis (QDA) [20]. This choice was based on a preliminary evaluation where we compared, Linear discriminant analysis (LDA) and QDA and found that the latter yielded slightly higher classification performance [19]. We report here results using a 4-fold cross-validation method which maintain the chronological order of the data [21]; i.e each fold corresponds to a separate run.

The performance of the single trial classification was evaluated using the area under the curve (AUC) in the receiver operating characteristics (ROC) space [22]. ROC curves show the trade-off between the false positive rates (FPR) and true positive rates (TPR) of the classifier for different decision thresholds. In our case, TPR is the portion of *Go* epochs that are classified as *Go* and FPR is portion of *No-go* epochs detected as *Go* epochs. The results of this analysis are described in Section 3.2.

2.3.2. Movement intention detection

In order to evaluate the possibility of using anticipatory SCPs for predicting the driver's movement intention, the performance of the classifier is tested in a moving window fashion. In this case, we pooled the data of *Drive* and *Brake* trials. It has been shown recently that there is a compromise between the value of the peak and its timing [16, 23]. Therefore, four different models/classifiers were built using the features extracted from a window of size 500 ms ending at different time points namely, at 200 ms (w1), 300 ms (w2), 400 ms (w3), and 500 ms (w4), respectively before the onset of the cues '3', '2', '1', and 'Start'/'Stop' (see Figure 2). Noting that, even though a smaller window has been used for this study, we still kept the same number of features; 4 equally spaced time points, in which the last one is the last time point of the window.

We tested the performance of these models using a sliding window with step of 62.5 ms, starting at 6 seconds before the onset of the imperative stimulus 'Start'/'Stop' (2 second before the appearance of the first cue '4') and ending at around 3 seconds after the movement. The performance of the decoder was evaluated by the *Go* detection rate (*GDR*), which is the percentage of the number of epochs, across all 4 folds, detected as *Go*. *GDR* is considered as a measure of movement intention. The predictive power of the decoder can be evaluated with the peak value of the *GDR* and the timing of the peak. In order to evaluate the significance of our detector performance in detecting the Go epochs, we generate a set of 'random classifiers' to estimate the 'chance level'. For that, we shuffle the training labels and perform 1000 times the 4-fold cross validation. Therefore, the Null hypothesis is that the results of the original classification can be drawn from a distribution generated by a set of random classifiers. If the classification performance is out of the 95% of the distribution, we reject the Null hypothesis.

3. Results

3.1. Event-related potentials (ERP)

Figure 3.a shows the EEG grand averages across all subjects (N=18) for both the *Drive* and *Brake* trials. The topographic plots of average scalp distribution show that the negativity is spatially localized in the central area and is maximal at centro-medial electrodes (especially Cz), which is consistent with existing literature on anticipation-related SCPs [7, 13, 24]. Additionally, note that the subjects reacted using the right foot, whose corresponding brain area is also under the same electrode [25].

In both *Drive* and *Brake* trials, we see a negative EEG deflection starting about 1 second before the appearance of the 'Start/Stop' cue; (i.e. around the onset of the last warning stimulus ('1' cue)), and peaking at about 0 s which is the time of the appearance of the 'Start/Stop' on the screen. 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 peak negativity is significantly higher for *Brake* trials than *Drive* (t-test, $p < 0.01$), where the peak negativity is estimated as the average of the potentials in individual trials from the window -200 ms to 0 s. The time point 0 s corresponds to presentation of the imperative stimulus 'Start'/'Stop'.

Figure 3.b shows the grand averages of the EMG envelopes. The onset of increasing activity in EMG is around -200 ms, confirming that there is no muscular activity of the leg (*tibialis anterior* muscle) during the preparation phase. The horizontal line shows

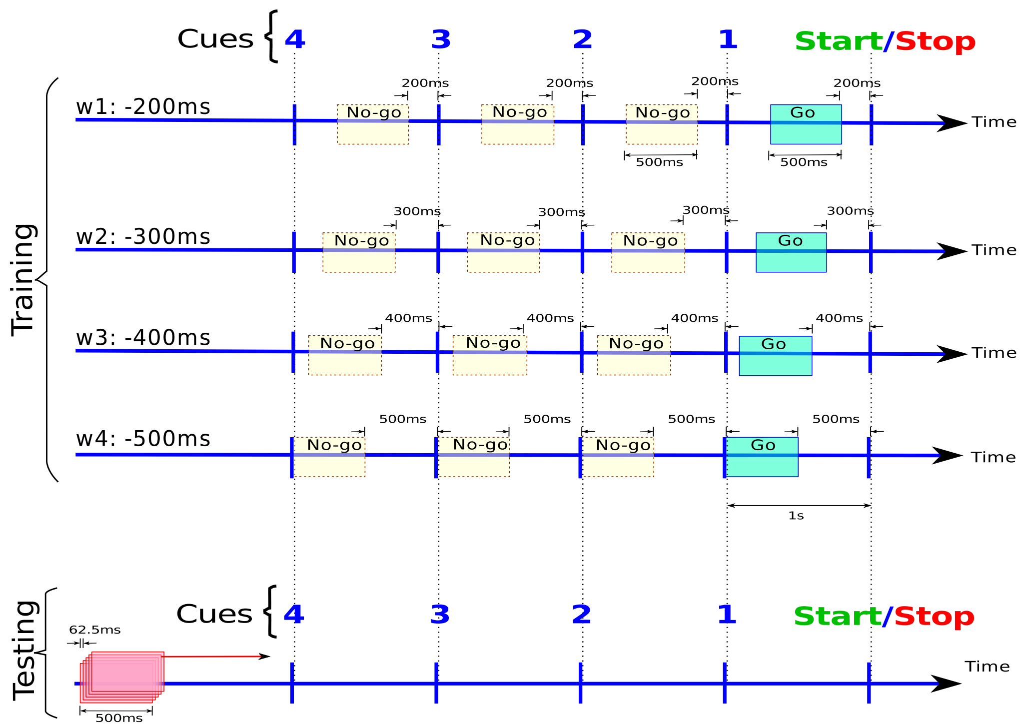

Figure 2. Training windows for the movement detection classifier. Four different models were built using the features extracted from a window of size 500 ms that ended at 200 ms (w1), 300 ms (w2), 400 ms (w3), and 500 ms (w4), respectively before the onset of the cues ('3', '2', '1', 'Start'/'Stop'). The segments that appeared before the warning stimulus were *No-go* epochs, whereas those appeared just before the imperative stimulus ('Start'/'Stop') were *Go* epochs. For testing (bottom trace), a similar window (500 ms) is used for extracting the features. Unlike the training phase, these windows were not time-locked but shifted with a step of 62.5 ms continuously.

the distribution of the timing of EMG onset for the *Drive* and *Brake* trials. This is defined as the time when the EMG activity exceeds a threshold equal to $\mu + 6\sigma$, where μ and σ are the mean and standard deviation of EMG signals of a one second window after the first warning cue (4) [26]. Theses results provide evidence that it is possible to observe anticipation-related EEG potentials during driving and before the muscular onset. As can be seen in Figure 3.a, a small negative deflection starting after the first warning stimulus ('4' cue) is also observed. The presence of a small negativity after the first warning stimulus and a relatively bigger negativity before the imperative stimulus (preceding the movement) is consistent with the bi-phasic negativity reported in previous studies on CNV potentials with a single pair of warning-imperative stimuli [7, 24].

3.2. Single trial classification

Figures 4 and 5 show the individual results of single-trial classification for *Brake* and *Drive* trials, respectively. The average AUC across subjects (N=18) is 0.83±0.13 for *Brake* trials. A slight decrease in performance is observed for *Drive* trials with an

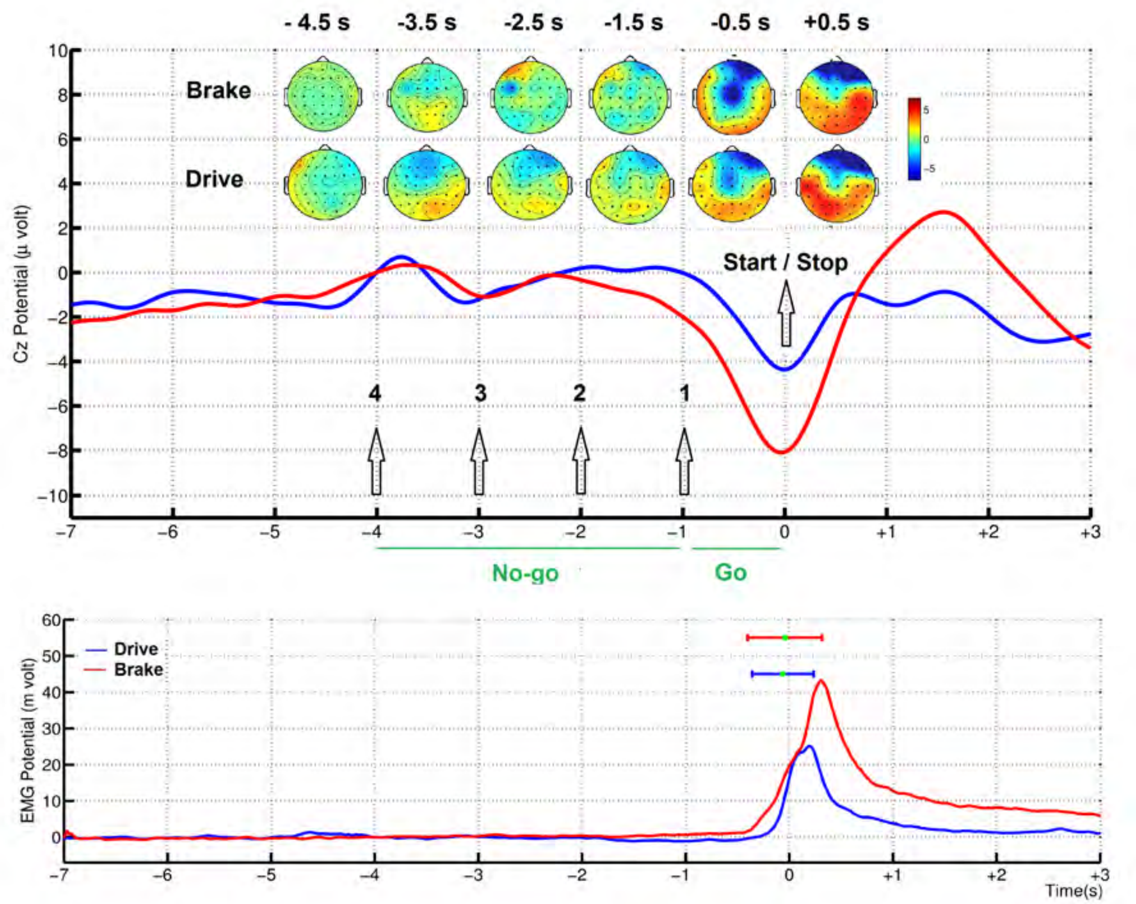

Figure 3. a) Anticipation-related SCPs. Top: Topographic representation of average EEG scalp distribution at different time points for *Drive* and *Brake* trials at 0.5 second before the onset of each cue which is shown by the arrow. Grand averages (N=18) of ERP for the Cz electrode, are shown in blue for *Drive* trials, in red for *Brake* trials. t=0 is the onset of the appearance of 'Start/Stop' cue and t=-4 is the onset of the appearance of the first count-down cue. b) Average of the envelop of the rectified EMG trace at *tibialis anterior* muscle to show the action execution. The horizontal line shows the distribution of the timing of EMG onset for Drive and Brake trials. The mean of of this distribution is shown with a green dot on top of each distribution. This figure is plotted using data of all subjects.

average AUC of 0.79±0.12 (t-test, p <0.01). Notably, 9 subjects reached an AUC above 0.90 for *Brake* trials, and 5 subjects for *Drive* trials.

The average AUC of *Brake* trials for *Group1* is 0.82±0.15 and for *Group2* is 0.84±0.13 (t-test, p=0.59). For *Drive* trials, the average AUC of *Group1* is 0.81±0.10 and for *Group2* is 0.76±0.12 (t-test, p=0.09). The comparison between the classification performance of *Group2* and *Group1* shows that classification performance of *Brake* trials is higher than *Drive* trials for *Group2*; while for *Group1*, the classification performance of *Brake* trials is very similar to *Drive* trials. Interestingly, the difference between *Drive* and *Brake* trials is larger for *Group2* (The recordings with RT feedback for *Brake* trials).

The classification results reported in Figure 4 and 5 are based on features from a single electrode (Cz). We also tested whether classification performance improves when information from several electrodes is taken into account. To this end, we choose a Bayesian fusion technique at the level of classifiers [13]. Alternatively, the fusion could have been applied at the level of features (e.g. putting together the features of different EEG channels). However, the latter requires a larger amount of data due to the increased feature dimensionality. Figure 6 shows the classification results for different combinations of electrodes. The electrode configurations are chosen by the order of increased Euclidean distance from the Cz electrode location. As can be seen in the Figure 6, increasing the number of electrodes lead to very similar classification performance to just using the Cz electrode (The configuration with three electrodes on a vertical line resulted in slightly higher AUC than just using a single electrode. However, the difference is not statistically significant). Hence, these results suggest that a single classifier trained with single electrode data is sufficient for the single trial classification. This can potentially be due to the pre-processing using the WAVG spatial filter, which corresponds to a smoothing function that includes the information of the surrounding electrodes.

Having demonstrated the feasibility of differentiating between the *Go* and *No-go* conditions in single trials based on the activity of the electrode Cz for both types of events (*Drive* and *Brake*), we further analyzed the temporal behavior of the classification. To this end, as described in Section 2.3.2, we tested the classifiers using features computed from moving windows across time from the Cz electrode potentials. Note that for the purpose of detection of movement intention, we pooled the data of *Drive* and *Brake* trials. We tested four different classifiers -each trained on different windows with respect to the stimulus onset (w1-w4; c.f., Section 2.3.2)- on features extracted from moving windows starting from -6 s till 3 s, where 0 s correspond to the appearance of imperative stimulus (i.e. 'Start'/'Stop' cue) and t=-4 s is the onset of appearance of the first stimulus '4' cue on the screen.

Figure 7 illustrates the results of the movement intention detection for each single subject using electrode Cz, and for the classification model trained based on the window w1 (ending at -200 ms before the stimuli). Each plot reports the average *Go detection rate (GDR)*, across the four test folds. Each point of the curve corresponds to the percentage of trials being detected as *Go* epoch, which we denote as a measure of movement intention at time *t*. The time points of the plot's x-axis correspond to the latest sample of the moving window decoded by the classifier. The chance level for each time point is calculated by shuffling the labels of the training data and performing 1000 times 4-fold cross validation (the mean of chance level in blue and the 95% confidence interval in blue shadow).

The *GDR* is above chance level for most participants (15 out of 18, except S5, S6, and S13) around the onset of the imperative stimulus. For all these participants, the *GDR* gradually raised above chance level and peaked earlier than the onset of imperative stimulus and the onset of movement. Interestingly, for most participants (e.g. S2) there exist another peak on the *GDR* around -3 s, which seem to signify detection of the early negativity of the CNV potential. Interestingly, we obtain low *GDR* values (except for S5, S6, and S15) in the periods of -6 s to -4 s and 1 s to 3 s, i.e. outside the windows used for training the classifier, suggesting the decoder has high specificity.

Figure 8 shows the peak *GDR* value for each window and its latency (the time when the highest performance is achieved) for the different training configurations (c.f. Figure 2). No statistical differences in the peak *GDR* were found across all training windows, what it is not the case for the latency (c.f., Figure 8). The earlier the training window, the earlier the *GDR* peak is detected. These results suggest that the movement intention can be detected based on the anticipation potentials as early as 320±200 ms before movement with an average detection rate of 0.77±0.12.

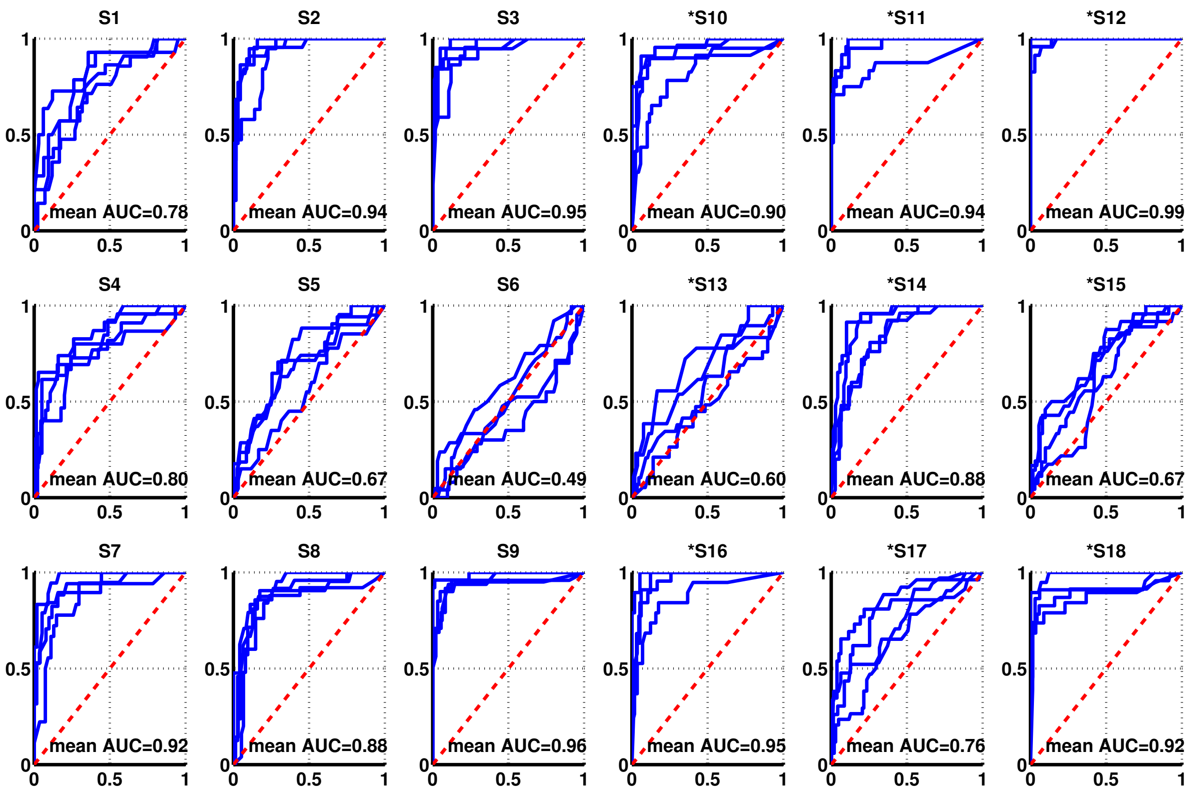

Figure 4. Individual classification performance for *Brake* trials. Subjects S1-S9, *Group 1*, did not receive RT feedback (S1-S6 with projection screen, S7-S9 with 3D screens), whereas subjects S10-S18, *Group 2*, with 3D screen and received RT feedback for the *Brake* trials. ROC curves and mean AUC values for all subjects (4-fold cross-validation). The dotted red line represents random performance and solid lines represents the ROC curves for each of the 4 folds. The mean AUC values are shown at the bottom of each ROC curve.

4. Discussion

In this study we investigated the existence of EEG correlates of anticipatory signals during driving. Firstly, the experiments conducted with 18 healthy participants shows that anticipatory event-related potentials, consistent with CNV signals reported in the literature [10, 11, 13], can be also observed in a simulated driving environment. Additionally, as can be seen in Figure 3.a, a small negative detection starting after the first warning stimulus ('4' cue) is also observed. The presence of a small negativity after the first warning stimulus and a relatively bigger negativity before the imperative stimulus (preceding the movement) is consistent with the bi-phasic negativity reported in previous studies with a single pair of warning-imperative stimuli [7, 24].

Secondly, although our experiments involve realistic settings —and not simple setups and stimuli as it is customary—, single-trial detection rates are promising. In the current experiment, the EEG signatures of anticipatory processes may be affected by visual distractors that naturally occur in driving tasks. Despite this, high performances up to an average AUC of 0.83±0.13 for discrimination between the *Go* and *No-go* epochs

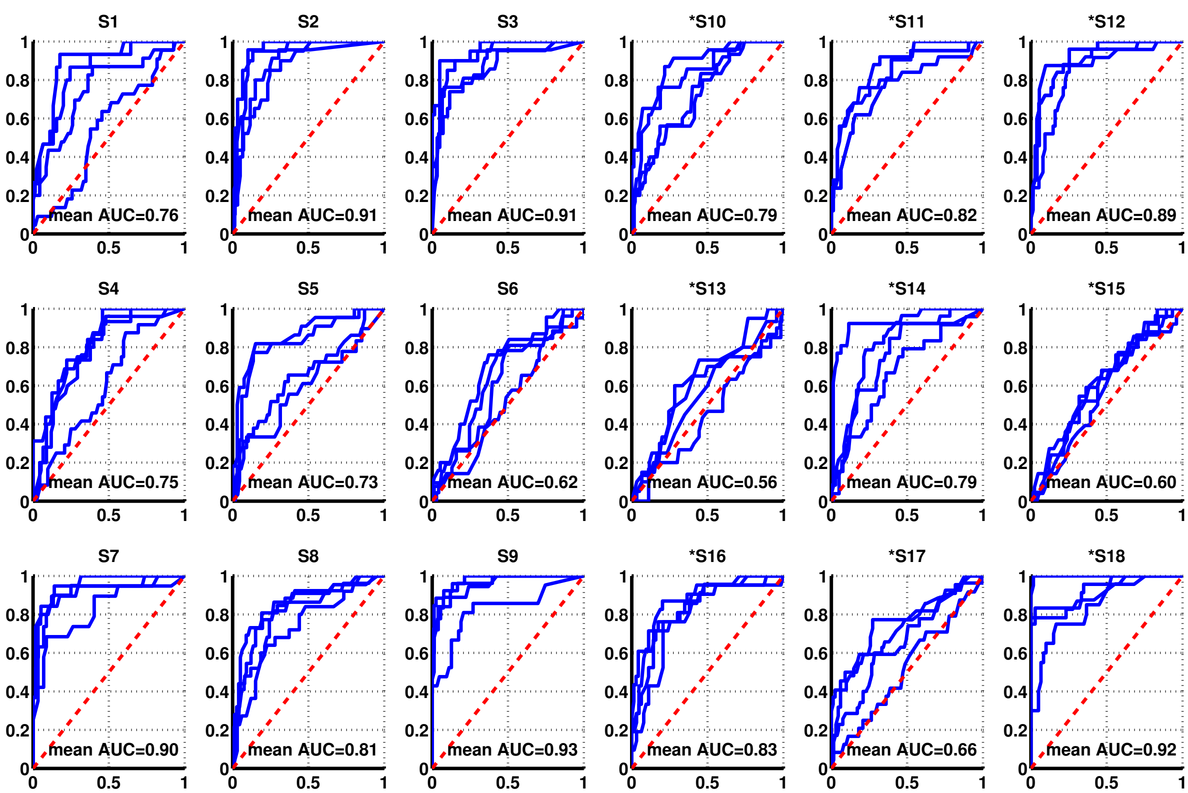

Figure 5. Individual classification performance for *Drive* trials. Subjects S1-S9, *Group 1*, did not receive RT feedback (S1-S6 with projection screen, S7-S9 used 3D screens), whereas subjects S10-S18, *Group 2*, used 3D screen and received RT feedback for the *Brake* trials. ROC curves and mean AUC values for all subjects (4-fold cross-validation). The dotted red line represents random performance and solid lines represent the ROC curves for each of the 4 folds. The mean AUC values are shown at the bottom of each ROC curve.

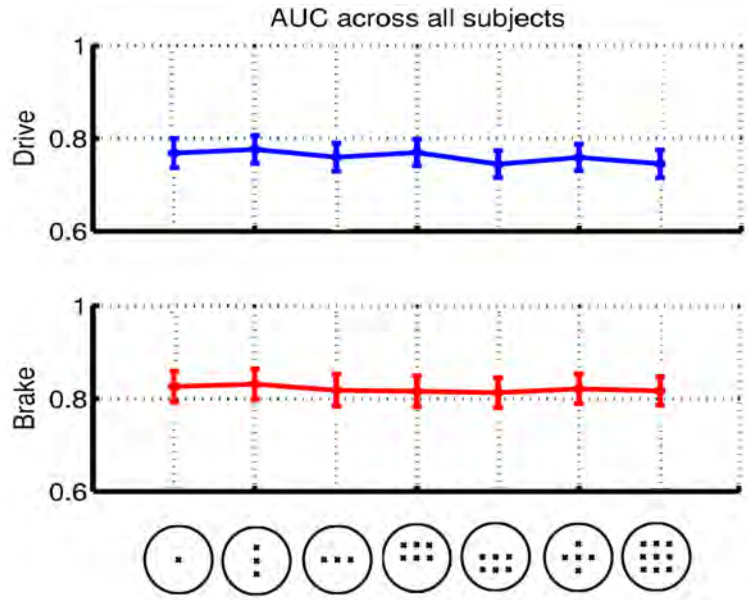

Figure 6. Average performance, AUC, across all subjects for different electrode configurations. The x-axis shows these electrode configurations in increasing the number of electrodes. The configuration with three electrodes on a vertical line resulted in slightly higher AUC than just using a single electrode. However, the difference is not statistically significant (t-test performed on the AUC values of *Drive* and *Brake* trials across 18 subjects)

for *Brake* trials have been achieved. We also observed a difference in the peak of the CNV potentials for the *Drive* and *Brake* trials. The *Brake* trials exhibit a larger negative peak, and classification results also show better performance compared to *Drive* trials (mean AUC of 0.79±0.12). One possible explanation for these difference concerns the kind of movement that is performed in each case: for *Drive* trials, the subject waits for the 'Go' signal with the foot already placed on the gas pedal and just needs to push it, whereas, for the *Brake* trials the subject has to first release the gas pedal, move the foot to the brake pedal and then push it.

Thirdly, movement detection using the moving window shows that these anticipatory potentials can be detected as early as 320±200 ms before the imperative stimulus with an average detection rate of 0.77±0.12 across 18 participants. Our results of movement intention detection from CNV potentials are in in-line with previous work on the self-paced movement intention detection [23, 15, 16]. Remarkably, we demonstrate low *GDR* values in the normal driving intervals (-6 s to -4 s and 1 s to 3 s), clearly outside the period of appearance of cues which is used for training. Such high specificity across time may be beneficial for online application.

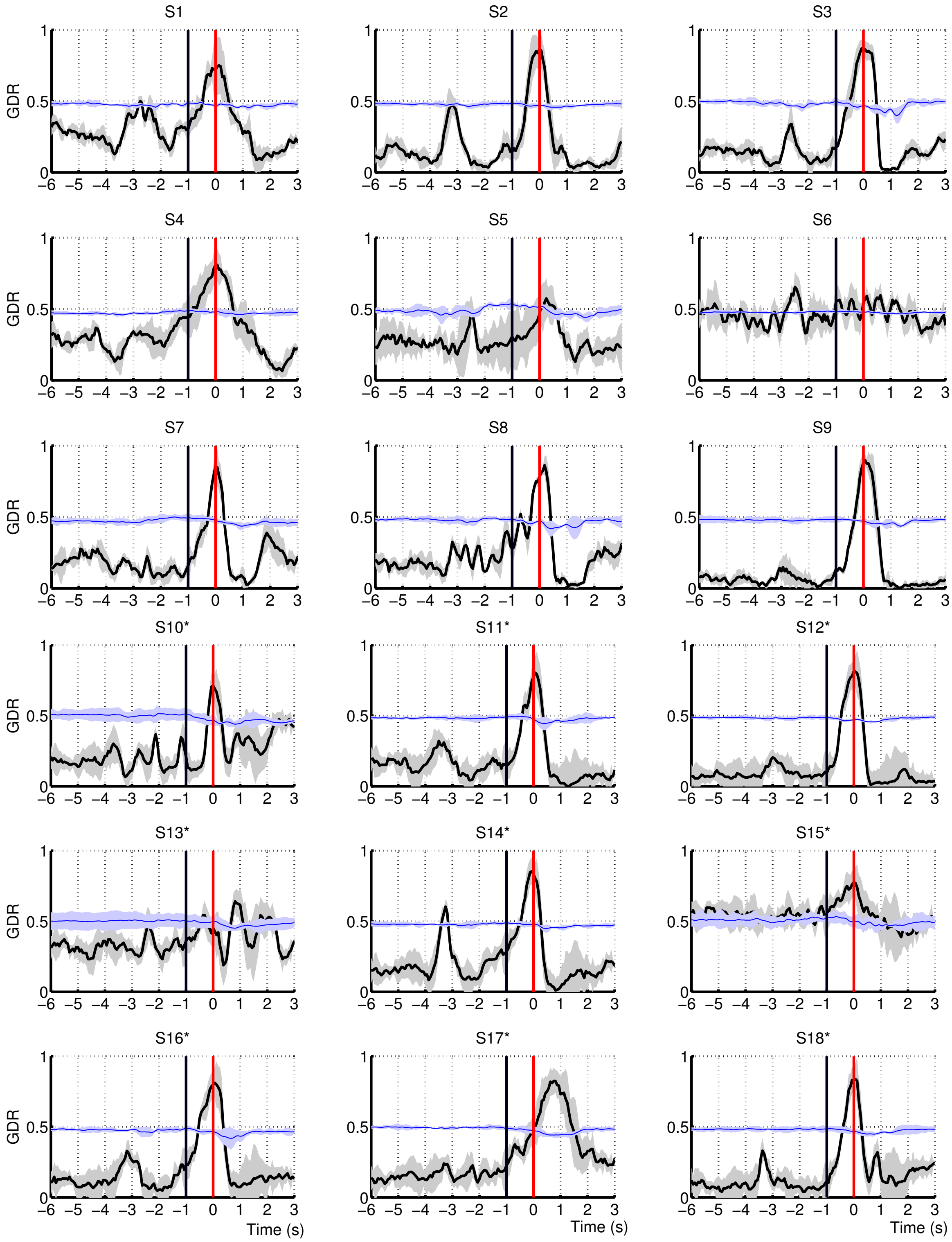

Figure 7. The results of movement intention detection through the *Go detection rate (GDR)* measure for all subjects. Classification performance is estimated using the training window ending -200 ms (w1) and testing during the time interval [-6,+3] s. The shaded region surrounding the average *GDR* illustrates the standard deviation at each point. The vertical red line in red color refers to the onset of the imperative stimulus; 'Start/Stop'. The black vertical line corresponds to the onset of the last warning stimulus. The chance level for each time point is calculated by shuffling the labels of the training data and performing 1000 times 4-fold cross validation (the mean of chance level in blue and the 95% confidence interval in blue shadow).

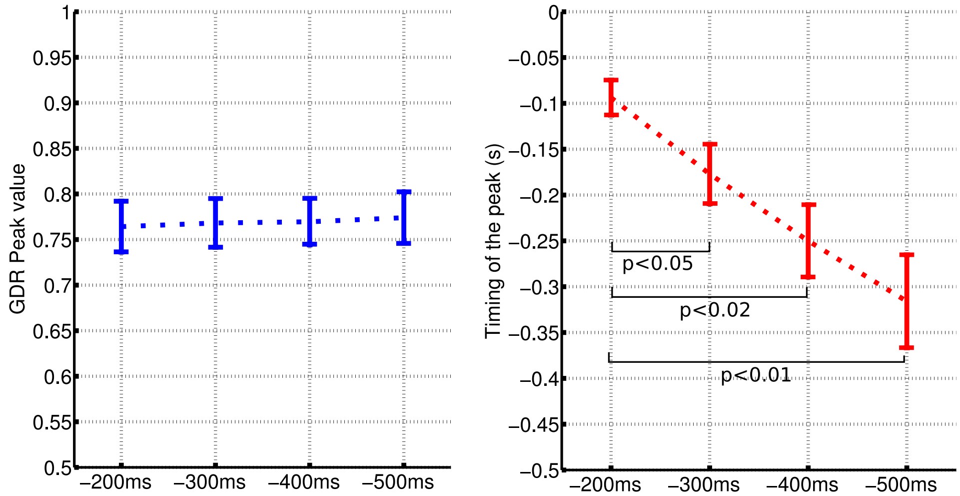

Figure 8. Performance of classifiers trained on different windows: on the left, the peak detection rates are indicated and on the right, the timing of the peak detection rates for various training windows (w1: 200 ms, w2: 300 ms, w3: 400 ms, w4: 500 ms). No statistical differences in the peak *GDR* were found across all training windows, what it is not the case for the latency. The earlier the training window, the earlier the *GDR* peak is detected.

5. Conclusions and Future works

This study presents and demonstrates the possibility of discriminating the anticipation-related potentials and predicting movement onset from scalp EEG during simulated car driving. It is worth noting that during the experiment, the subjects needed to process changing visual inputs. The immediate future step, before testing our methods in a real car, is to conduct online experiments with more realistic driving scenarios (real traffic lights, inclusion of other vehicles) to assess the real-time detection of anticipatory signals. Complementary to other approaches for the early detection of movement onset or intention to move by means of various EEG correlates appearing in self-paced movement tasks [15, 17, 16], we are the first, to the best of our knowledge, to prove the possibility of predicting the subject's voluntary intention in response to external events during driving (e.g. the count-down warning cues resemble the traffic lights in real driving) by means of detecting anticipatory brain potentials. This approach also complements other efforts on decoding neural correlates during driving tasks, in particular, the recent study on the detection of the intention of emergency braking [4, 5, 6]. Our results support the feasibility of BCI systems for future cars in order to predict the driver's movement intentions. Predicting the driver's will can be beneficial as the driving assistance system will be aligned with the driver's intention. Thus, in the scenario of the traffic lights described in this paper, the driving assistance system can exploit the BCI output to provide support as follows. In the case that the driver is not aware of the traffic light changing colors, no anticipatory brain potentials are generated and the BCI detects no intention to execute a movement. The driving assistant could then provide a warning to the driver who would have time to brake by himself, preventing the car to generate an emergency brake at the last moment that may cause him a negative surprise. On the other hand, detecting the planned action before its execution also brings advantages as it enhances the driver's experience: it will ensure a seamless interaction between the car and the driver, promoting the car to behave as a truly extension of driver's body.

6. Acknowledgement

The work was supported by Nissan Motor Co. Ltd., under the 'Research on Brain Machine Interface for Drivers'. The authors would like to thank Gangadhar Garipelli, Huaijian Zhang, and Serafeim Perdikis for their valuable comments and help with the design of the experimental protocol, as well as valuable discussions regarding the analysis and proofreading.

References

[1] 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 *International Joint Conference on Neural Networks*, 2010, pp. 1–7.

[2] 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 *International Symposium on Circuits and Systems*, 2010, pp. 2287–2290.

[3] C. Dijksterhuis, D. de Waard, K. Brookhuis, B. Mulder, and R. de Jong, "Classifying visuomotor workload in a driving simulator using subject specific spatial brain patterns." *Frontiers in Neuroscience*, vol. 7, no. 149, 2013.

[4] 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.

[5] S. Haufe, J. Kim, I. H. Kim, A. Sonnleitner, M. Schrauf, G. Curio, and B. Blankertz, "Electrophysiology-based detection of emergency braking intention in real-world driving," *Journal of Neural Engineering*, vol. 11, no. 5, p. 056011, 2014.

[6] I. H. Kim, J. W. Kim, S. Haufe, and S. W. Lee, "Detection of braking intention in diverse situations during simulated driving based on EEG feature combination," *Journal of Neural Engineering*, vol. 12, no. 1, p. 016001, 2015.

[7] 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*, vol. 203, pp. 380–384, 1964.

[8] R. De Charette and F. Nashashibi, "Real time visual traffic lights recognition based on spot light detection and adaptive traffic lights templates," in *IEEE Intelligent Vehicles Symposium*, 2009, pp. 358–363.

[9] M. Omachi and S. Omachi, "Traffic light detection with color and edge information," in *2nd IEEE International Conference on Computer Science and Information Technology.* IEEE, 2009, pp. 284–287.

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

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

[12] 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*, 2012.

[13] G. Garipelli, R. Chavarriaga, and J. d. R. Millán, "Single trial analysis of slow cortical potentials: a study on anticipation related potentials," *Journal of Neural Engineering*, vol. 10, p. 036014, 2013.

[14] N. Birbaumer, T. Elbert, A. G. Canavan, and B. Rockstroh, "Slow potentials of the cerebral cortex and behavior," *Physiological Reviews*, vol. 70, pp. 1–41, 1990.

[15] I. Niazi, N. Jiang, O. Tiberghien, J. Nielsen, K. Dremstrup, and D. Farina, "Detection of movement intention from single-trial movement-related cortical potentials," *Journal of Neural Engineering*, vol. 8, p. 066009, 2011.

[16] E. Lew, R. Chavarriaga, S. Silvoni, and J. d. R. Millán, "Detection of self-paced reaching movement intention from EEG signals," *Frontiers in Neuroengineering*, vol. 5, p. 13, 2012.

[17] R. Xu, N. Jiang, C. Lin, N. Mrachacz-Kersting, K. Dremstrup, and D. Farina, "Enhanced low latency detection of motor intention from EEG for closed loop brain computer interface applications," *IEEE Transactions on Biomedical Engineering*, vol. 61, no. 2, pp. 288–296, 2014.

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

[19] Z. Khaliliardali, R. Chavarriaga, L. A. Gheorghe, and J. d. R. Millán, "Detection of Anticipatory Brain Potentials during Car Driving," in *34th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2012, pp. 3829–3832.

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

[21] N. Bourdaud, R. Chavarriaga, F. Galán, and J. d. R. Millán, "Characterizing the EEG correlates of exploratory behavior," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 16, no. 6, pp. 549–556, 2008.

[22] T. Fawcett, "An introduction to ROC analysis," *Pattern recognition letters*, vol. 27, no. 8, pp. 861–874, 2006.

[23] L. Gheorghe, R. Chavarriaga, and J. d. R. Millán, "Steering timing prediction in a driving simulator task," in *35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2013, pp. 6913–6916.

[24] N. Loveless and A. Sanford, "The impact of warning signal intensity on reaction time and components of the contingent negative variation." *Biological Psychology*, vol. 2, no. 3, p. 217, 1975.

[25] G. Pfurtscheller, C. Neuper, C. Andrew, and G. Edlinger, "Foot and hand area mu rhythms," *International Journal of Psychophysiology*, vol. 26, no. 1-3, pp. 121–135, 1997.

[26] D. Bilt and D. Glas, "Detection of onset and termination of muscle activity in surface electromyograms," *Journal of Oral Rehabilitation*, vol. 25, no. 5, pp. 365–369, 1998.