Anticipation Based Brain-Computer Interfacing (aBCI)

Garipelli Gangadhar, Ricardo Chavarriaga, and José del R. Millán

***Abstract*—Anticipation increases the efficiency of daily tasks by partial advance activation of neural substrates involved in it. Previous off-line studies have shown the possibility of exploiting this activation for a Brain-Computer Interface (BCI) using electroencephalogram (EEG). In the current paper we report real-time and single trial recognition of this activation using a prototype of anticipation based BCI (aBCI). We report on-line classification accuracies with peak values of 85% and 80%, and with average values of $69.0 \pm 7.9\%$ and $58.5 \pm 14.1\%$ for subjects 1 and 2, respectively. Posterior off-line analysis showed improved accuracies for both subjects, with an average of $80.5 \pm 10.1\%$ and $69.0 \pm 10.5\%$ with peak values of 95% and 85% respectively.**

***Index Terms*—Anticipation, brain-computer interaction (BCI), contingent negative variation (CNV), electroencephalogram (EEG).**

I. Introduction

Anticipation increases the efficiency of daily tasks by partial advance activation of the neural substrates involved [1]. Recent off-line studies on the single trial recognition of these potentials from electroencephalogram (EEG) show the possibility of developing an anticipation based Brain-Computer Interface (aBCI) [2], [3]. For example, consider a scenario of navigating a brain-actuated wheelchair [4] along a corridor towards a goal room. Using its onboard proximity sensors, the intelligent wheelchair can detect the presence of a doorway, but it cannot decide whether to enter into the room or continue along the corridor. However, the user can make the appropriate decision by anticipating the presence of the target room. Before realizing such a pragmatic application it is necessary to assure the reliability of real-time on-line recognition of these potentials in a closed loop. The current paper is aimed at studying such an aBCI with a simple prototype.

To record anticipation related potentials we adopted the classical Contingent Negative Variation (CNV) paradigm [5] as experimental procedure. A vast amount of literature describes the CNV potentials (the potentials recorded using CNV paradigm) as related to anticipation [5]–[7]. In this paradigm, a warning stimulus (S1) predicts the appearance of an imperative stimulus (S2) in a fixed inter-stimulus-interval (ISI). A negative shift in the cortical activity with a centro-medial distribution (under the vertex electrode, Cz) usually develops between S1 and S2 depending on contingency of stimuli and task parameter relevance [6], [7] (see Fig.1 for the CNV protocol with GO and NOGO conditions and EEG grand averages). This signal has been shown to be stable over several days and in different conditions (e.g., amount of sleep time) [6]. In addition, an early neurofeedback experiment suggests that humans are able to modulate it [8]. The stability of this potential, and the human's ability to modulate its amplitude, support the possibility of using this phenomenon for the design of aBCI.

One of the challenges of exploiting these potentials for a BCI is to recognize them on single trials and to obtain classifiers that have good generalization capabilities over time. Previous studies shown the feasibility of recognizing these potentials in single trials by exploring several classification

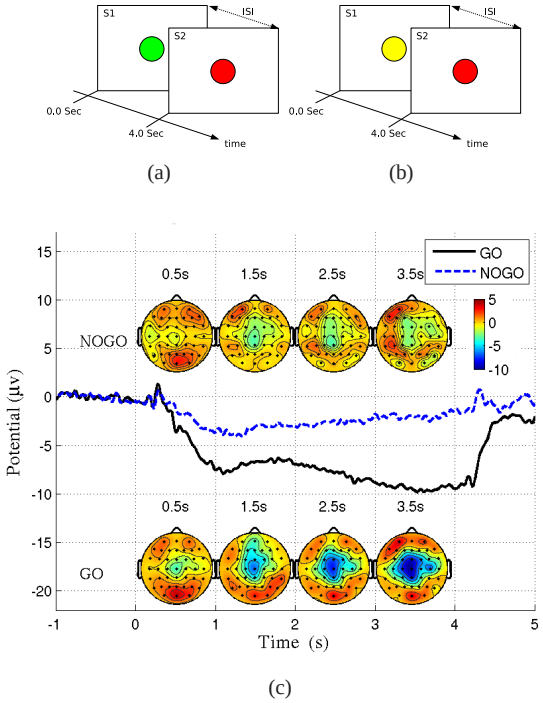

Fig. 1. Contingent Negative Variation (CNV) paradigm used in the calibration phase and ERP grand averages. (a) In the GO condition a warning stimulus (S1) with a green dot at time $t = 0s$ is displayed and then an imperative stimulus (S2) with a red dot is presented with ISI of 4s. Subjects are instructed to anticipate and press a button as soon as S2 is presented. (b) To differentiate the NOGO condition from the GO condition S1 is replaced with a yellow dot. The subjects are instructed to do nothing for this condition. (c) The grand average ERPs of GO (solid line) and NOGO (dashed line) trials are shown for Cz electrode. The circular figures are the topographic representation of average scalp distribution at different time scales for GO (bottom) and NOGO (top) conditions (computed using EEG of 6 subjects; reproduced from previous studies [2])

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techniques [2]. In another study it has been shown that these slow-cortical potentials are not only recognizable reliably on single trials but also fast [3]. The current paper makes further progress by testing real-time recognition with a similar method and feedback in a simple closed-loop prototype of aBCI application.

In the next section we describe the phases of aBCI closed-loop prototype along with the EEG preprocessing and classification techniques. In section III we first discuss the results of real-time recognition and feedback of these potentials. We then discuss the off-line analysis of these EEG potentials aiming at further improvement of classification accuracies. In section IV we discuss our future steps in realizing a pragmatic application of aBCI.

II. Methods

The development of the aBCI prototype consists of two phases; first, a *calibration phase*, in which we train classifiers based on EEG potentials recorded with the CNV protocol (see Fig.1). Then, in the *evaluation phase*, subjects pass through a similar protocol in which they anticipate without providing a motor response, and the classifiers built in the previous phase are used on-line to recognize the user's intent. It is worth noting that the training is a very fast procedure and we started the evaluation phase approximately 10 min after the calibration phase. These phases are described in detail in the following paragraphs.

A. Calibration phase

In this phase we compute the classifiers for on-line use in the next phase. During this phase we recorded EEG of two subjects performing CNV protocol with 100 trials per condition. The EEG signals were acquired using 64 electrodes according to the 10/20 international system with a sampling rate of 512Hz. The EEG was spatially filtered using common average reference and baseline activity computed as average activity during [-1 0]s. To compute a reliable classifier we removed some trials which are believed to contaminate the best training samples with the following criteria:

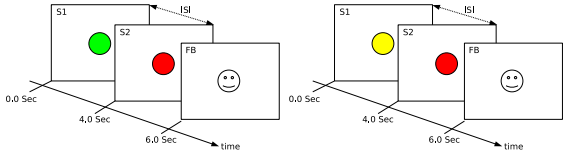
1) A GO trial is included only if the anticipation response time (RT) w.r.t the S2 appearance is in the range of [-0.15 0.15]s for subject 1 and [-0.2 0.2] sec for subject 2 (30 trials for subject 1 and 48 trials for subject 2 were included).
2) A NOGO trial is included if the peak negative value is above -20μ volts (30 trials for subject 1 and 30 trials for subject 2 were included).

These heuristics were based on the reasoning that the RT and amount of negativity correlates with the GO condition (in other words, better anticipation leads to shorter RT and higher negativity at central electrodes).

For selected training trials, we computed a linear polynomial approximation of the activity at Cz electrode in the interval [0 3.25]s as suggested by previous studies [2]. The coefficients of this polynomial were used as features and a Linear Discriminant Analysis Classifier (LDA) [9] is calculated for each subject and used in the next phase.

B. Evaluation phase

In this phase we test on-line the classifiers calculated in the previous phase in a modified CNV paradigm that does not require any muscular response (see Fig. 2). The difference in the CNV paradigm between the previous phase and current phase is that the subject does not have to press any button but simply need to anticipate for the appearance of S2 (for the GO condition alone). At the end of each trial, feedback is shown based on the classification result 2s after the appearance of S2 (i.e., a happy smiley is shown if correctly recognized and a sad smiley otherwise). This phase replaces motor commands by mental commands decoded by the aBCI. We recorded 10 evaluation sessions each containing 10 trials per condition for both subjects. We also recorded an extra session for subject 1 after a gap of 20 min.



(a) (b)

Fig. 2. Evaluation phase (a) GO condition; similar to Fig. 1(a) except the subjects are instructed to anticipate for the appearance of S2 without providing any motor response. (b) NOGO condition; same as Fig. 1(b). Based on the on-line classification a feedback is provided 2s after the appearance of S2.

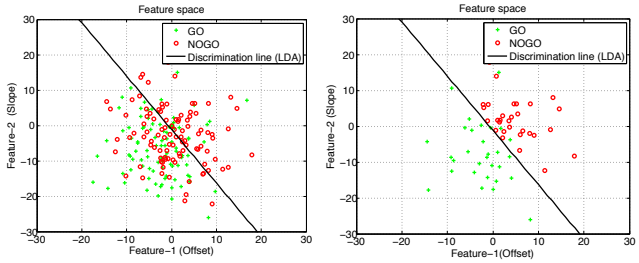
III. Results

In this section we first report the results of real-time recognition of anticipation related potentials using the aBCI prototype. We then report further off-line analysis of the recorded EEG potentials for improving the classification methods aimed at future applications.

A. Real-time classification results

As mentioned in the previous section we first cleaned some of the calibration trials to obtain best training trials to ensure high training accuracy so that the feedback from the aBCI system is as accurate as possible to help the subject's conditioning. Comparison of training accuracies for different polynomial orders ($n \in 1, 2, 3, 4, 5, 6$) revealed linear approximation (n=1; the slope and offset of the signal as features) as the best order with training classification accuracies of 95% and 88.3% for subjects 1 and 2, respectively. It is worth noting that the cleaning step eliminated the overlapping regions of the class distributions (see Fig. 3).

The on-line classification results of each evaluation session are shown in Fig. 4. Performances above random classification were obtained in all sessions for subject 1 and in most sessions for subject 2, with peak accuracies reaching up to 80%. Four out of 11 sessions and 3 out of 10 sessions achieved performances above 70% for subject 1 and 2 respectively. Average classification accuracy of $69.0 \pm 7.9\%$ for subject 1 and $58.5 \pm 14.5\%$ for subject 2 were observed. From the dashed lines in Fig. 4, one can notice that the system performance increases during the first few sessions (1-3 for subject 1 and



(a) (b)

Fig. 3. Feature distributions of calibration phase for subject 1. The features are the slope and offset of linear approximation of a line to the EEG potentials at Cz electrode. (a) before cleaning (b) after cleaning. The discriminative line is computed using a LDA classifier.

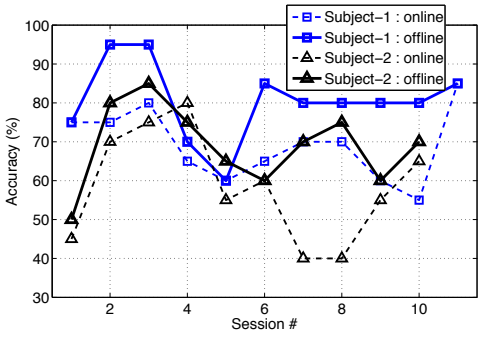
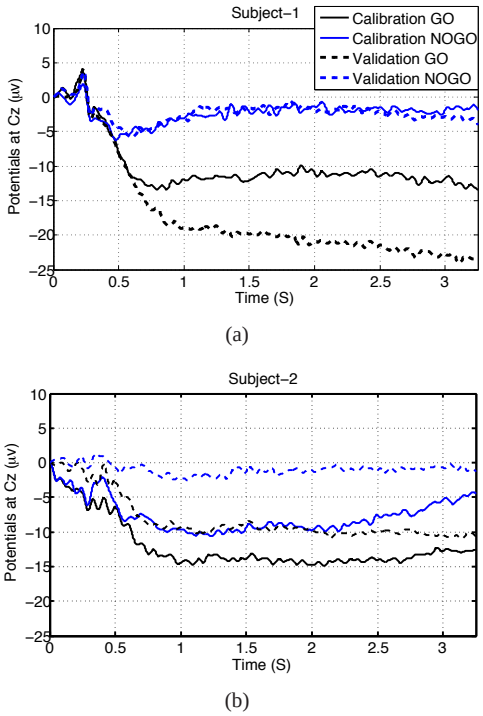


Fig. 4. Realtime on-line classification accuracies obtained in the evaluation sessions for the two subjects are shown in dotted line. Offline classification accuracies are shown in solid line.



(a)

(b)

Fig. 5. Grand averages ERP of GO (black) and NOGO (blue) trials in the calibration phase (solid line) and evaluation phase (dashed line) computed for the Cz electrode potentials. (a) subject 1. (b) subject 2.

1-4 for subject 2), suggesting that subjects are able to generate stable and more separable signals over a certain period of time (particularly evident in the case of subject 2). However, the performance in the next five sessions decreases with respect to the initial sessions. In general, system errors are mainly due to misclassification of the NOGO condition. Performance degradation may be the result of subject's fatigue, as well as reduced motivational levels, as suggested by post-experimental interviews with the subjects. Moreover, the subject 1 achieves an accuracy of 85% in an extra session after a break of 20 min (see Fig. 4).

B. Off-line analysis

In this section we first report the changes in grand averages due to BCI feedback during the evaluation phase in comparison to the calibration phase. Then we discuss improvement in the classification accuracies with a different strategy as future perspective.

1) Grand average ERPs of aBCI: Previous off-line studies showed an increasing trend in the classification accuracy over sessions [2]. Based on this observation, we have hypothesized that BCI feedback may help the subjects to learn to generate better discriminable patterns. In the current aBCI experiment we can observe specific changes in the grand-average ERPs due to BCI feedback (see Fig. 5). The ERPs corresponding to GO and NOGO condition appear farther apart in the evaluation phase compared to the calibration phase for both subjects. It is a clear indication of subject's conditioning. It also suggests that on-line adaptation may be required to track such changes in EEG for better BCI performance [10].

2) Improvements in classification accuracies: We believed that classifiers with high training accuracy may help the subject's conditioning, which we obtained by eliminating some trials based on behavioral and neuphysiological criteria (see section II). However, posterior off-line analysis of the recorded EEG data of calibration and evaluation phases, where we explored higher order polynomial features suggests that cleaning of the trials was not necessary. In this analysis we observed a decrease in the training accuracies (obtained using calibration trials without cleaning) but a significant improvement in the test accuracies (trials of evaluation phase) for both subjects (on average, $80.5 \pm 10.1\%$, $69.0 \pm 10.5\%$ for subject 1 and 2, respectively, with an improvement of approximately 10%). The comparison between the off-line and on-line sessions shows an improvement in almost all sessions for both subjects (9 out of 11 for subject 1 and 8 out of 10 for subject 2). Peak accuracies reach 95% and 85% for subject 1 and 2, respectively (see Fig. 4). We can also observe the similar increase in the first few sessions for both subjects. However, during the later sessions for subject 1 the performance is very stable (sessions 6-11) and significantly better for subject 2 (sessions 7 and 8). As in the on-line analysis, the best polynomial order was selected by comparing training accuracy of classifiers trained for each order between 1 and 6 (i.e., using the trials of the calibration phase). In this case the best orders were 6 and 4 for subjects 1 and 2, respectively. The average classification accuracies over evaluation sessions obtained using different polynomial orders

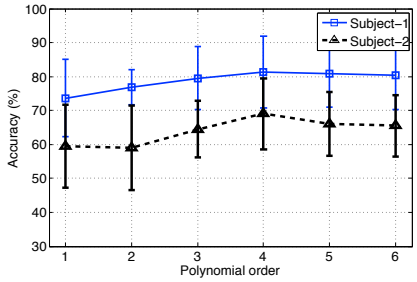


Fig. 6. Offline analysis using different polynomial orders. Average classification accuracies achieved for different polynomial orders approximated for the potentials of Cz electrode for subjects 1 and 2.

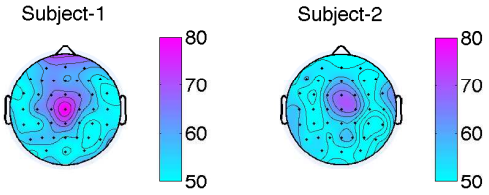


Fig. 7. Off-line analysis using all the evaluation trials. Topographies of single electrode test accuracies computed for subject 1 and 2.

is shown in Fig. 6. From the figure it is noticeable that the best performances are achieved with the order selected with the calibration trials.

Neurophysiological studies suggest that CNV is observed predominantly at Cz electrode. However, the correlates of anticipation can be observed at other electrodes sites in fronto-central areas during the early peak and centro-parietal areas during the later peak (see Fig. 1). As a future perspective we assess the discriminability of all the remaining electrodes separately using the same methods. The results confirm that Cz electrode is the best for both subjects (see Fig. 7). However, since other electrode signal features are also discriminable, a future step can be to explore multi-electrode features for achieving more robust classifiers.

IV. Discussion

Previous studies on single trial recognition of anticipation related potentials argued that anticipatory behavior can be exploited for developing BCI. However, it is necessary to test real-time recognition of these methods in a closed loop before going for a pragmatic application. In this paper we make such an attempt by testing real-time recognition and feedback of anticipation related potentials using a simple prototype of aBCI. This prototype consists of two phases, first a calibration phase during which classifiers were calculated and an evaluation phase during which the classifiers were tested and a feedback was presented. In this phase we observed the peak accuracies of 85% and 80% for subject 1 and subject 2, respectively with an average over test sessions of $69.0 \pm 7.9\%$ and $58.5 \pm 14.1\%$. We observed an increase in the system performance during the first evaluation sessions, suggesting subject's adaptation to the BCI. However, there is a performance degradation in the later sessions which may be the result of subject's fatigue. Further off-line analysis of the recorded data using different strategies shows significant improvements in accuracies for both subjects in almost all evaluation sessions with peak values of 95% and 85% with average of $80.5 \pm 10.1\%$ and $69.0 \pm 10.5\%$ for subject 1 and 2, respectively.

As hypothesized, we noticed specific changes in the EEG during the evaluation phase as compared to the calibration phase. The grand averages in evaluation session were farther apart. This is likely due to the BCI feedback of the recognition which possibly helped the subject to adapt.

From the results reported in the previous section the following strategies have to be adopted for the next step in realization of a realistic aBCI application. First, the features need to be computed using higher order polynomial approximation. Second, cleaning of the trials for ensuring high train accuracy may not be a necessity. Third, classifiers computed using feature selection methods applied to multiple electrodes along with Cz electrode may lead to more robust classifiers. Fourth, on-line adaptation of classifiers may help in tracking changes EEG due to subject's learning. Lastly, as the simplicity of the experimental task seems to fail in keeping the subject's attention, we need to conduct experiments in a more engaging, realistic setup such as navigation of a robotic wheelchair in virtual environments.

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