Fast Recognition of Anticipation Related Potentials

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. Here we develop a method for the recognition of electroencephalogram (EEG) correlates of this activation as early as possible on single trials which is essential for Brain-Computer Interaction (BCI). We explore various features from the EEG recorded in a Contingent Negative Variation (CNV) paradigm. We also develop a novel technique called Time Aggregation of Classification (TAC) for fast and reliable decisions that combines the posterior probabilities of several classifiers trained with features computed from temporal blocks of EEG until a certainty threshold is reached. Experiments with 9 naive subjects performing the CNV experiment with GO and NOGO conditions with an inter-stimulus interval of 4 s show that the performance of the TAC method is above 70% for four subjects, around 60% for two other subjects, and random for the remaining subjects. On average over all subjects, more than 50% of the correct decisions are made at 2 s, without needing to wait until 4 s.**

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

I. Introduction

ANTICIPATION is a process that not only depends on past and current states but also on future expectations. It increases the efficiency of daily tasks by partial advance activation of neural substrates involved in those tasks [1]. The recognition of this activation can be exploited for Brain-Computer Interaction (BCI). For example, consider a scenario of navigating a brain-actuated wheelchair [2] 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. Furthermore, fast recognition of the user's anticipatory mental state is essential to guide the wheelchair to the goal before it misses the doorway.

To the best of our knowledge anticipation related potentials in human EEG are well studied in the context of clinical science and functional neurophysiological studies, but not well explored in the context of BCI excepting one early attempt based on neurofeedback [3]. Here we present a method for fast recognition of these potentials as a first step towards the design of an anticipation-based BCI.

To record anticipation EEG potentials we have used a classical Contingent Negative Variation (CNV) paradigm [4]–[6]. In this paradigm a warning stimulus (S1) predicts the appearance of an imperative stimulus (S2) in a predictable inter-stimulus-interval (ISI). A negative shift in cortical activity with a centro-medial distribution (under the vertex electrode, Cz) usually develops between S1 and S2 depending on contiguity of stimuli and task parameter relevance. This anticipation potential is usually composed by an early deflection around 1s and a late deflection prior to S2 based on the latency of the stimuli [5]. This signal has been shown to be reliable and stable over several days and in other conditions (e.g., amount of sleep hours) [6]. In addition, neurofeedback experiments suggest that humans are able to modulate its amplitude [3]. The stability of this potential and human's ability to modulate its amplitude support the possibility of using this phenomenon for the design of an anticipation-based BCI. To this end, it is first necessary to ascertain the feasibility of fast and reliable recognition of anticipation potentials on single trials. This is the goal of the current study.

The paper is structured as follows. Next section describes the experimental protocol, EEG acquisition and grand averages. Section III describes the features we have explored and different classification techniques, with a focus on a novel method for fast recognition. Section IV reports the classification results. Finally, Section V gives some conclusions and discusses future steps for building an anticipation-based BCI.

II. Methods

In this section we describe the experimental setup and CNV paradigm. We then briefly explain EEG preprocessing and discuss grand averages.

A. Experimental setup and behavioral paradigm

The CNV paradigm with relevant (GO) and irrelevant (NOGO) conditions triggers anticipatory and non-anticipatory behaviors, respectively. The EEG signals of nine male subjects (22-27 yrs.) were recorded in four consecutive sessions with 50 trials in each session (equiprobable GO and NOGO trials in random order separated by an inter-trial interval of 4 ± 4 s). Fig. 1(a) and Fig. 1(b) describe the CNV paradigm used in the current study.

B. Data acquisition and preprocessing

EEG potentials were acquired with a portable system (Biosemi Active Two) using 32 (3 subjects) or 64 (6 subjects) electrodes according to the 10/20 international system. The

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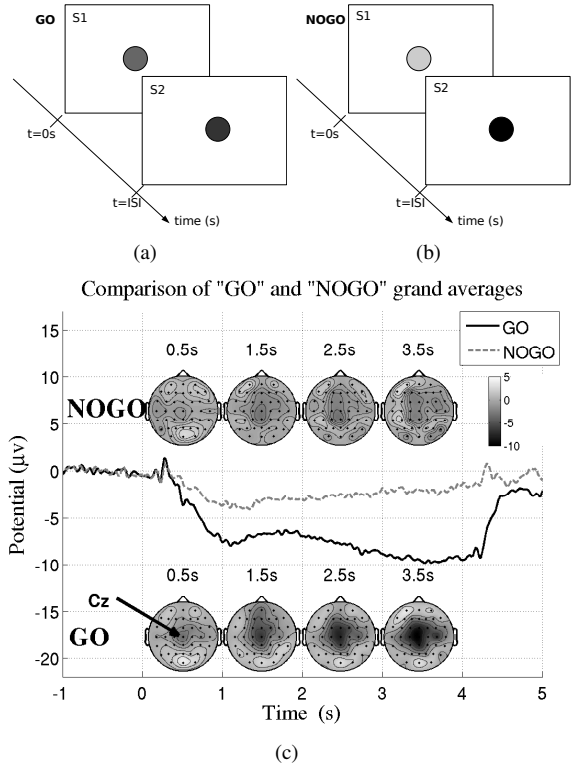


Fig. 1. The CNV experimental setup and grand averages. (a) For the GO condition a warning stimulus (S1) with a green dot at time $t = 0s$ and then an imperative stimulus (S2) with a red dot on the screen is presented with ISI of 4s. The subjects are instructed to anticipate and press a button as soon as S2 is presented. (b) In the NOGO condition S1 is a yellow dot and subjects are instructed to do nothing. (c) The grand averages of GO and NOGO trials for six subjects recorded with the 64-electrode configuration at Cz electrode. The circular figures are the topographic representation of average scalp distribution at different times for GO (bottom) and NOGO (top) conditions.

sampling rate was 512 Hz and signals were re-referenced using a common average reference (CAR). The potentials were then filtered using a low pass filter with cut off frequency of 15 Hz. For each electrode, we removed its baseline activity, computed as its mean potential during [-1 0] s.

C. EEG grand averages

The EEG grand averages at Cz electrode computed over all the subjects for the recordings with the 64-electrode setup (see Fig. 1(c)) show clear differences for GO and NOGO conditions. From the topographic plots of average scalp distribution we can observe the increasing negativity under this electrode in the GO condition. An evoked response due to S1 is observed around 0.3 s to 0.4 s in both conditions. The potential at Cz during the GO condition is composed of an early peak around 1.0 s and a late peak between 3.5 s and 4.0 s, which are consistent with previous studies [5]. Similar grand averages are observed in the case of recordings with 32 electrodes. Although clear differences are observed in grand averages, the use of anticipation potentials for BCI imposes the challenge of recognizing them as early as possible on a single trial basis. The methods developed for addressing these challenges are described in the next section.

III. Classification methods

As the subjects were instructed to press a button on the arrival of S2 (at 4 s), the recognition methods only work on the EEG potentials up to 3.5 s after the onset of S1 so as to avoid any movement preparation potential that could contaminate the recognition of anticipation processes [7]. Furthermore, and given the clear focus of the anticipation potentials, for the current work we restrict to features computed only from the Cz electrode. In the following subsections we describe methods for computing features $\{x\}$ and classification techniques based on the potentials recorded at this electrode ($v_{Cz}(t)$, where t is time, $t \in [0 \;\; T_{max}]$ and $T_{max} = 3.5$ s).

A. Feature extraction

We have explored two kinds of features to describe anticipation EEG potentials, namely Least Square Fitting Line (LSFL) features and Least Square Fitting Polynomial (LSFP) features.

1) Least square fitting line (LSFL): Bozinovski and Bozinovska [3] used the slope of EEG potentials at Cz for recognizing CNV in their neurofeedback experiment. Instead of just the slope m, we explored LSFL features that also includes the offset c ($\tilde{v}_{Cz} = mt + c$). The feature vector is then described as $x = [c \;\; m]^T$.

2) Least square fitting polynomial (LSFP): We further explored higher order features such as the coefficients of n^{th} order LSFP (α_i, $\tilde{v}_{Cz} = \alpha_0 + \alpha_1 t^1 + \ldots + \alpha_n t^n$). Each trial is then described by the feature vector $x = [\alpha_0 \;\; \alpha_1 \;\; \alpha_2 \;\; \ldots \;\; \alpha_n]^T$.

B. Feature projection & classification

The feature vectors x are first projected onto a canonical space $y \in R$ by using $y = \mathbf{W}^T x$ ($\mathbf{W}$ is a projection matrix that maximizes the between-class variance and at the same time minimizes the within-class variance) for better separation before applying classification techniques. The $\mathbf{W}$ matrix is computed by maximizing Fisher's criterion [8],

$$J(\mathbf{W}) = \frac{\mathbf{W}^T \mathbf{S_B} \mathbf{W}}{\mathbf{W}^T \mathbf{S_W} \mathbf{W}} \tag{1}$$

where $\mathbf{S_B} = (\mu_{\mathcal{C}_2} - \mu_{\mathcal{C}_1})(\mu_{\mathcal{C}_2} - \mu_{\mathcal{C}_1})^T$ is the *between-class* covariance matrix and $\mathbf{S_W} = \sum_{l \in \mathcal{C}_1} (x_l - \mu_{\mathcal{C}_1})(x_l - \mu_{\mathcal{C}_1})^T + \sum_{l \in \mathcal{C}_2} (x_l - \mu_{\mathcal{C}_2})(x_l - \mu_{\mathcal{C}_2})^T$ is *within-class* covariance matrix, where x_l is the feature vector of the l^{th} trial, $\mu_{\mathcal{C}_1}$ and $\mu_{\mathcal{C}_2}$ are the mean vectors of classes $\mathcal{C}_1$ (for GO) and $\mathcal{C}_2$ (for NOGO), respectively. Now, maximizing J($\mathbf{W}$) and neglecting the magnitude of W we obtain $\mathbf{W} = {\mathbf{S_W}}^{-1}(\mu_{\mathcal{C}_2} - \mu_{\mathcal{C}_1})$ [8].

A QDA classifier [8] is trained on the features projected onto the canonical space. For a given trial the posterior probabilities for the two classes are computed as

$$p(\mathcal{C}_i|y) = \frac{p(y|\mathcal{C}_i)p(\mathcal{C}_i)}{\sum_j p(y|\mathcal{C}_j)p(\mathcal{C}_j)} \tag{2}$$

where $i, j \in \{1, 2\}$. The prior probabilities $p(\mathcal{C}_i)$ for each class are set to 0.5 and the likelihood is computed as

$$p(y|\mathcal{C}_i) = \frac{1}{\sqrt{2\pi {\sigma_{\mathcal{C}_i}}^2}} exp(-\frac{(y - \mu_{\mathcal{C}_i})^2}{2{\sigma_{\mathcal{C}_i}}^2}) \tag{3}$$

where $\mu_{\mathcal{C}_i}$ and $\sigma_{\mathcal{C}_i}$ are the mean and variance of the projected features of the class $\mathcal{C}_i$, respectively. Finally, a trial is assigned to the class with the highest posterior probability.

C. Time aggregation of classification

The methods described in the previous section can make a decision only after 3.5 s. However, early recognition of EEG patterns is advantageous for building a real-time BCI. Lemm et al. [9] proposed a method for online recognition of motor imagery aimed at aggregating classification accuracy across time. In their technique they combine the posterior probabilities of a sequence of classifiers, each built for every time point using different kinds of features. Instead of computing features at every time point, using a large sequence of classifiers, we propose a technique that aggregates posterior probabilities of a few classifiers trained on different blocks of EEG signals. This technique is called TAC, for *time aggregation of classification*.

The TAC posterior probability, $P(\mathcal{C}_i|y_{\{1,2\ldots k\}})$, at time step k is computed by aggregating (by multiplication and normalization) the posterior probability of an individual QDA classifier ($P(\mathcal{C}_i|y_k)$) with the previously accumulated posterior probability ($P(\mathcal{C}_i|y_{\{1,2\ldots k-1\}})$) as

$$\begin{aligned} p(\mathcal{C}_i|y_{\{1,2,\ldots k\}}) &= p(\mathcal{C}_i|y_k, y_{\{1,2\ldots k-1\}}) \\ &= \frac{p(\mathcal{C}_i|y_k)p(\mathcal{C}_i|y_{\{1,2,\ldots k-1\}})}{\sum_j p(\mathcal{C}_j|y_k)p(\mathcal{C}_j|y_{\{1,2\ldots k-1\}})} \end{aligned} \quad (4)$$

where $k \in \{1, 2 \ldots N\}$, N is the maximum number of steps or number of classifiers and $y_{\{1,2\ldots k\}}$ represents the canonical projections, $y_1, y_2 \ldots y_k$ of feature vectors, $x_1, x_2 \ldots x_k$ that are assumed to be independent.

At each time step $p(\mathcal{C}_i|y_{\{1,2\ldots k\}})$ is compared with a confidence threshold (p_τ) and a decision is made as soon as the posterior probability of one of the classes is higher than p_τ. If at the final step N no probability is above p_τ, then the decision is the class with the highest posterior probability.

In the current paper we report experiments based on $N = 7$ decision points, where each of the classifiers is trained with features computed at every 0.5 s (i.e., at time steps $T_k = 0.5$ s, 1.0 s $\ldots$ 3.5 s for $k \in \{1, 2 \ldots 7\}$), either in overlapping or non-overlapping windows. For the overlapping case (TAC-OL), the classifiers are trained on features computed at every 0.5 s using the potentials from 0 s to T_k (i.e., [0 0.5] s, [0 1.0] s $\ldots$ [0 3.5] s). In the non-overlapping case (TAC-NOL), the 7 classifiers are trained on features computed with windows of 0.5 s from the previous time step to current time step (i.e., [0 0.5] s, [0.5 1.0] s $\ldots$ [3.0 3.5] s).

IV. Results

To assess the performance of the methods across time we used the first 3 sessions as training set and the fourth session as testing set. The classification results are summarized in Table I. It is worth noting that for all the methods tested in the current study there is no significant differences between recordings with 32 (subjects 4, 5 and 9) or 64 electrodes (remaining subjects). The value of p_τ and the polynomial order are selected independently for each subject using ROC analysis on the training set. For p_τ we explored probability values in the range $[0.8 \quad 0.975]$, whereas for the polynomial order the values were $n \in \{2, 3, 4, 5, 6\}$ (the highest polynomial order was 6 because of the small amount of training samples).

TABLE I
Performances (% of classification accuracy) of features, classifiers, and TAC methods. {L,P}-{FQ,Q}: LSFL or LSFP features, Fisher projection plus QDA or QDA alone classifiers

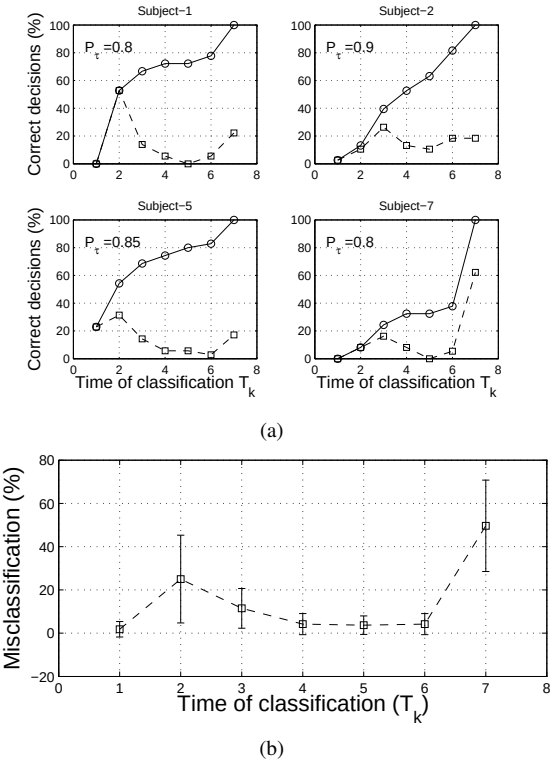
Subject	L-FQ	P-FQ	P-Q	TAC-NOL	TAC-OL
1	73.5	69.4	61.2	79.6	73.5
2	79.6	75.5	65.3	79.6	77.6
3	43.8	58.3	45.8	60.4	56.3
4	42.0	56.0	60.0	56.0	60.0
5	65.3	71.4	63.3	71.4	71.4
6	42.0	40.0	40.0	54.0	50.0
7	46.0	70.0	66.0	74.0	74.0
8	50.0	45.8	39.6	43.8	52.1
9	40.0	52.0	50.0	38.0	40.0

A. Single-trial recognition

We first compared the performance of LSFL and LSFP features, which were first projected onto a canonical space, using a QDA classifier. Although LSFL shows higher accuracies for some subjects (e.g., subjects 1 and 2), overall LSFP features outperform LSFL features, especially if we remove subjects whose performance is random (Wilcoxon test, p=0.05). This indicates that LSFP features describe anticipation related potentials better than simple LSFL features. On average over all the subjects, the best polynomial order for LSFP features was 5.4 ± 0.7. Secondly, we compared the performance of this classification method, Fisher projection plus QDA, against QDA alone. Table I shows that projection significantly improves performance (Wilcoxon test, p=0.02). Thirdly, we checked the sensitivity of performance to preprocessing steps such as CAR and low-pass filtering. Performances are not significantly different without these steps. Possible reasons are that, since the CNV is a slow potential, removing the baseline filters out background activity similarly to the CAR and that LSFP features, whose highest order is 6, filter out high frequencies.

B. Fast recognition using TAC

Since LSFP features outperformed LSFL features, we used the former for studying the performance of the TAC-OL and TAC-NOL. Both methods perform equally well and show a significant improvement over QDA classifiers (Wilcoxon test, p=0.05). TAC not only improves the classification accuracy but also yields faster decisions. For instance, as shown in Fig. 2(a) with the TAC-OL method, for those subjects whose performance is above 70% (1, 2, 5 and 7), 72.7%, 52.6%, 74.3% and 32.4%, respectively, of the correct decisions are made by the end of 2 s ($T_k = 4$) without waiting until the final point ($T_k = 7$). Fig. 2(b) shows the percentage of misclassification averaged over subjects 1, 2, 5 and 7, illustrating the benefit of a high confidence threshold P_τ that yields a low percentage of early misclassifications. However, there is an increase of misclassification at the final decision



(a)

(b)

Fig. 2. Results of TAC-OL for subjects 1, 2, 5 and 7. (a) Average percentage of correct decisions made at time T_k, dotted line, and average percentage of correct decisions accumulated at T_k, solid line. Panels show the confidence threshold P_τ selected for each subject. (b) Average percentage of misclassifications at each decision point over the four subjects.

point $T_k = 7$ where we forced a decision to be made. The results with TAC-NOL are similar.

V. Conclusions

In the current paper we have reported techniques for the fast and reliable classification of anticipation related potentials from human EEG as a first step towards the design of an anticipation-based BCI. Our off-line study shows that LSFP features computed using potentials at Cz electrode outperform LSFL features that are frequently reported as features of CNV potentials [3], [10]. We introduced a novel TAC method for aggregating classification accuracy across time using multiple classifiers trained on temporal EEG blocks. This technique permitted increased accuracies (up to 80%) with fewer amount of EEG data for most of the trials. It is also worth noting that all the subjects considered in the current study had no previous experience with the CNV protocol. Since CNV is a learned paradigm we believe that chance level accuracies for some subjects is due to lack of experience with the protocol. Since early neurofeedback studies show that subjects were able to learn to modulate these potentials, the closed loop implementation of TAC method for a BCI (which we consider as a future work) should improve the classification performance. In addition, we will extend the TAC method to multi-electrode features. Finally, the classification method developed in this paper can be exploited for early recognition of other slow cortical potentials.

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