Recognition of Anticipatory Behavior from Human EEG

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Abstract

Anticipation increases the efficiency of a daily task by partial advance activation of neural substrates involved in it. Single trial recognition of this activation can be exploited for a novel anticipation based Brain Computer Interface (BCI). In the current work we compare different methods for the recognition of Electroencephalogram (EEG) correlates of this activation on single trials as a first step towards building such a BCI. To do so, we recorded EEG from 9 subjects performing a classical Contingent Negative Variation (CNV) paradigm (usually reported for studying anticipatory behavior in neurophysiological experiments) with GO and NOGO conditions. We first compare classification accuracies with features such as Least Square fitting Line (LSFL) parameters and Least Square Fitting Polynomial (LSFP) coefficients using a Quadratic Discriminant Analysis (QDA) classifier. We then test the best features with complex classifiers such as Gaussian Mixture Models (GMMs) and Support Vector Machines (SVMs).

1 Introduction

Anticipation is a process that not only depends on past and current states but also on future expectations. Without anticipation everyday cognitive tasks would become exclusively reactive. Conversely, this process increases the efficiency of daily tasks by partial advance activation of the neural substrates involved [1]. We hypothesize that the recognition of this activation can be exploited for Brain Computer Interaction (BCI). For example, consider a scenario of a brain-actuated wheelchair [2] driving towards a table with breakfast lying among several other tables. Using the onboard sensors the intelligent controller in the wheelchair can detect the presence of a table in front but it cannot decide by itself whether to dock or avoid. If the controller is integrated with anticipation recognition algorithms, the user can issue the docking command just by anticipating the docking event to happen. Otherwise, the controller triggers the obstacle avoidance behavior.

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 [3] but not well explored in the context of BCI, excepting one early attempt based on neurofeedback [4]. In the current work we compare different methods for the recognition of these potentials on single trials as a first step towards the design of an anticipation-based BCI.

To record these potentials we have considered a classical Contingent Negative Variation (CNV) paradigm [3] as an experimental procedure. A vast amount of literature describes the CNV potentials (the potentials recorded using CNV paradigm) as related to anticipation [3, 5, 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 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 [5, 6]. This signal has been shown to be stable over several days and in different conditions (e.g., amount of sleep time) [5]. In addition,

one neurofeedback experiment suggests that humans are able to modulate its amplitude [4]. 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 anticipation-based BCI. To this end, it is first necessary to ascertain the feasibility of achieving reliable recognition of CNV potentials on single trials; this is the goal of the present study. In the following sections we describe the experimental setup, along with classification techniques used in recognizing these potentials.

2 Methods

2.1 Experimental setup

We used the CNV paradigm with relevant (GO) and irrelevant (NOGO) conditions for simulating anticipatory and non-anticipatory behaviors (e.g., the table with food corresponds to a relevant condition). Fig. 1(a) and Fig. 1(b) describe the CNV paradigm used in the current study. The EEG signals of nine male subjects (22-27 yrs.) were recorded in four consecutive sessions with 50 trials each (equiprobable GO and NOGO trials in random order separated by an inter-trial interval of $4 \pm 4s$).

2.2 Data acquisition and preprocessing

The EEG signals were acquired for 9 subjects using 32 (subjects 4, 5 and 9) or 64 (remaining 6 subjects) electrodes according to the 10/20 international system with a sampling rate of 512Hz. Raw EEG signals were first spatially filtered by using common average reference (CAR). The signals were then filtered using a low pass filter with cut off frequency of 15Hz and then the trials were extracted and separated into GO and NOGO trials using S1 as the reference (i.e., onset of S1 considered as at 0.0s) with [-1.0 5.0]s as total trial interval. Average voltage of the time window from -1000ms to 0ms was used as a baseline.

2.3 EEG grand averages

The EEG grand averages at Cz electrode computed over subjects for GO and NOGO conditions show clear differences (see Fig. 1(c) for grand averages using 64 electrode set-up). Similar differences are observed in the case of 32 electrode set-up. From the topographic plots of average scalp distribution we observed an increasing negativity under this electrode in GO condition and a smaller negativity in NOGO condition. An evoked response due to S1 is observed at this electrode around 0.3s to 0.4s in both conditions. The potential at Cz during GO condition is composed of an early peak around 1s and a late peak between 3.5s and 4.0s which is consistent with previous studies [6]. Although clear differences are observed in grand averages, the use of these potentials for BCI imposes the challenge of recognizing them on single trial. The methods developed for addressing these challenges are described in the next section.

3 Classification

As the subjects were instructed to press a button on the arrival of S2 (at 4s) the recognition methods evaluated here are based on the EEG potentials up to 3.5s after the onset of S1 (0.0s) in order to avoid any movement preparation potential that could contaminate the recognition of anticipation processes. In the scope of the current work we restrict to features computed from the potential at Cz electrode alone ($v_{Cz}(t)$, where t is time, $t \in [0 \;\; T_{max}]$ and $T_{max} = 3.5s$).

3.1 Feature selection

Since slope and peak negativity are usually reported as features of CNV potentials [1], we first test Least Square Fitting Line (LSFL) parameters with the help of a Quadratic Discriminant

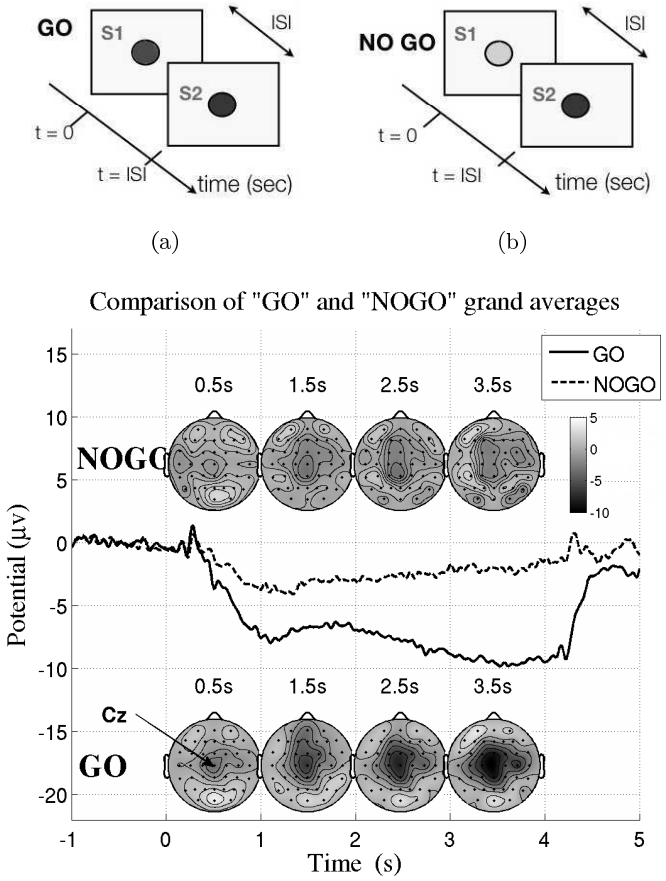

Figure 1: CNV experimental setup and ERP grand averages. (a) In the GO condition a warning stimulus (S1) with a green dot at time $t = 0s$ is displayed and then an imperative stimulus (S2) with a red dot on the screen is presented with ISI of 4s. Subjects are instructed to anticipate and press a button 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 averages of GO and NOGO trials for six subjects recorded with 64 electrode configuration at Cz electrode. The circular figures are the topographic representation of average scalp distribution at different time scales for GO (bottom) and NOGO (top) conditions.

Analysis (QDA) classifier. We then compare higher order features such as Least Square Fitting Polynomial (LSFP) features computed as the coefficients of n^{th} order LSFP (α_i, where i= 1,...n of $\tilde{v}_{Cz} = \alpha_0 + \alpha_1 t^1 + \alpha_2 t^2 + \ldots + \alpha_n t^n$). Each trial is then described by feature vector, $\mathbf{x} = [\alpha_0 \;\; \alpha_1 \;\; \alpha_2 \;\; \ldots \;\; \alpha_n]^T$, where, $\mathbf{x} \in \mathbb{R}^{n+1}$. The best polynomial order for each subject is chosen by comparing training accuracies of classifiers calculated for $n \in \{2, 3, ..., 6\}$ (the maximal order for search is 6 due to the limited amount of training samples). The LSFL features are equivalent to the LSFP features with order one.

3.2 Classifiers

We compare classification of anticipation related potentials using the features described above with the help of different classifiers described in the following paragraphs. Due to space limitations we give only a very brief introduction of these classifiers.

Quadratic Discriminant Analysis (QDA). Similar to Linear Discriminant Analysis (LDA) classifier, the QDA classifiers assumes that the features are normally distributed and relaxes the assumption that the covariance of each class is identical. For the current problem, we first project the features onto a canonical space with the help of a projection matrix, that maximizes between-class variance and minimizes within-class variance, which can be obtained by maximizing Fisher's criterion [7]. We then calculate QDA classifiers on the projected features.

Gaussian Mixture Model (GMM). The GMM is a generative model widely used for clustering and classification applications. In the current study we first model each class distribution with a separate GMM and using these models we build a classifier. The initial estimates of means are obtained using a k-means algorithm and we then use the Expectation Maximization (EM) algorithm [7] for estimating the mean ($\boldsymbol{\mu_k}$), covariance ($\boldsymbol{\Sigma_k}$) and mixing coefficients (π_k) of each Gaussian component of the GMM. Due to limited number of training samples we reduce the number of free parameters to estimate by constraining the covariance matrix to be diagonal and sharing it among all the components. The best number of Gaussian components for each subject is obtained by exhaustive search in the range {1, 2, ..., 4} based on training accuracies. Since this classifier suffers from the problem of local minima for complex data that are not well clustered, we built 100 different models with random initial Gaussian centers. The best model from all the 100 models was then chosen using the training accuracy and considered for testing with test data.

Support Vector Machine (SVM). SVMs are supervised learning methods that simultaneously minimize empirical classification error and maximize the geometrical margin between two classes [8]. In the present study we report classification results based on linear kernel (SVM-linear) and Radial Basis Function kernel (SVM-RBF). The free parameters of the classifier are estimated by 10-fold cross validation on training trials.

4 Results

To assess the classification performance across sessions we did a 4-fold cross-validation study where each fold corresponds to a separate session. The results of this study are summarized in Table 1. We first did feature comparison with the help of QDA classifiers trained separately for each subject. We observed that the LSFP features outperform the LSFL features (Wilcoxon test p=0.01, over all the subjects and sessions), suggesting that these features describe the anticipation related potential better than the LSFL features that are usually computed for the characterization of the CNV potential in neurophysiological studies [1, 4]. It is worth noting that no specific differences are observed for EEG setup with 32 or 64 electrodes.

Since LSFP features performed better, we tested them on the other complex classifiers such as GMM and SVM-linear and SVM-RBF classifiers to compare with the performance of the QDA classifier (see Table. 1). The classification accuracies of the QDA classifier are significantly better than the other three classifiers (Wilcoxon test, p=0.01 among all the subjects and sessions). Coming to individual subjects, the accuracies for subjects 6, 8 and 9 are close to random for all the methods. For subjects 1, 2, 3 and 5 the QDA classifier with LSFP features performed significantly better than the other classifiers (the best being subject 5, 75.86±6.45%). On average the SVM classifier with linear kernel is the next best classifier. However, this classifier gives accuracies above 65% only for one subject whereas the QDA classifier does so for 3 subjects. The SVM classifier with RBF kernel and GMM classifier perform worse compared to the QDA classifier.

Although the QDA classifier with LSFP features performs best compared to all the other methods, the results of cross-validation show that the recognition method is not reliable enough for a BCI. Nevertheless, most subjects exhibit an increasing performance over sessions (we excluded the subjects 6, 8 and 9 from this study due to the classification accuracies are close to random in all sessions with all the classifiers). Fig. 2 illustrates this trend with the help of accuracies averaged over all the 6 subjects separately for each session. The accuracies in the 3^{rd} and 4^{th}

Table 1: Comparison of cross-validation accuracies with different features and classifiers.

	LSFL	**LSFP**			
Subject	**QDA**	**QDA**	**GMM**	**SVM-linear**	**SVM-RBF**
1	62.15±8.62	66.14±6.78	58.02±9.44	58.02±5.69	58.52±7.92
2	64.61±13.17	66.04±6.90	64.55±5.68	64.55±6.31	54.37±5.44
3	47.57±5.56	59.91±10.97	46.87±1.82	46.87±7.37	45.93±7.68
4	50.50±5.74	58.00±7.48	61.00±5.29	61.00±12.48	51.00±3.83
5	68.83±8.95	75.86±6.45	66.31±7.36	66.31±6.60	46.73±4.11
6	53.64±8.40	53.09±9.55	43.54±4.00	43.54±6.43	52.44±3.03
7	44.64±3.01	54.77±11.93	57.04±7.20	57.04±10.03	53.75±4.44
8	53.82±9.39	51.28±4.25	44.01±9.09	44.01±9.36	47.11±6.40
9	51.00±8.08	51.00±5.29	51.00±9.59	51.00±12.70	53.00±8.25

session are significantly higher ($67.06 \pm 12.30\%$ and 66.77 ± 7.77) as compared to the first two sessions (58.60 ± 13.96 and 61.37 ± 5.61). Observing this trend, we argue that the features of this potential are becoming stable and well separable over time due to subjects adaptation to the experimental paradigm. This suggests that, similar to BCI systems, a good training method is a key component for subjects to learn to provide stable EEG patterns. Proper training of the subjects is likely to enhance the classification accuracies with the methods studied in the current work.

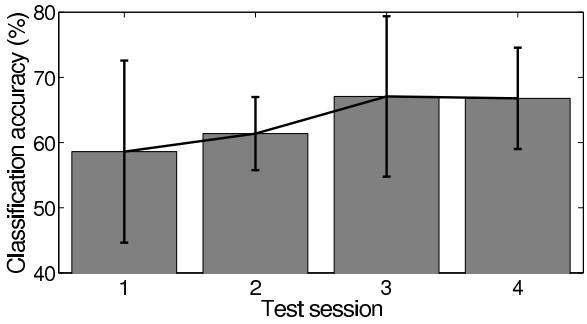

Figure 2: Average classification accuracies in different sessions using QDA classifier with LSFP features for subjects 1-5 and 7.

5 Conclusions

We compared different classification techniques for the recognition of anticipation related potentials from human EEG as a first step towards the design of a novel BCI. From the off-line studies on these potentials using the QDA classifier we observed that the LSFP features perform better than the LSFL features. This result suggests that LSFP features describe the anticipation related potential better than the LSFL features, the latter being those usually computed in neurofeedback and neurophysiological studies for the characterization of CNV potentials [4, 1]. We also compared the classification accuracies of LSFP features with QDA, GMM, SVM-linear and SVM-RBF classifiers. The 4-fold cross validation, with each fold corresponding to a separate session, showed that the QDA classifiers perform significantly better than the other classifiers

It is worth noting that none of the subjects considered in the current study had previous experience with the CNV protocol. The systematic observation of the performance in each session

showed an increasing trend in classification accuracy for most (6 out of 9) subjects. We argue that this trend is due to subjects' adaptation to the experimental paradigm. However, for the remaining subjects the classification accuracy is at chance level which is most likely due to lack of practice (note that the CNV paradigm is a learned task and subjects need to practice for a few sessions). As some subjects learn faster than others the classification accuracies also differ in the same way. Moreover, as there is a learning component, the classifier calculated using the later sessions does not perform well for the early session, whereas the classifier calculated using early sessions performs better for the later session (see Fig. 2).

Proper training of the subjects is likely to enhance the performance of the recognition methods compared in the current study. Moreover, an early study based on neurofeedback showing that the subjects were able modulate these potentials [4]. Based on this knowledge we hypothesize that the closed loop implementation of the current recognition methods can improve the subject's training yielding to more stable and well separable features. We consider this implementation as next immediate step for further research. In addition, we will extend these methods to multi-electrode features in order to improve the classification accuracies. Also, fast recognition of these potentials is another crucial factor for building a reliable BCI application. We plan to achieve this by extending the current methods to multi-classifier based recognition techniques in which each classifier looks at different temporal blocks of EEG and makes a decision as quickly as possible.

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References

[1] G.J.M. Van Boxtel and K.B.E. Böcker. Cortical measures of anticipation. *Journal of Psychophysiology*, 18:61–76, 2004.

[2] G. Vanacker, J. del. R. Millán, E. Lew, P. Ferrez, F. Galán, J. Philips, H. V. Brussel, and M. Nuttin. Context-based filtering for assisted brain-actuated wheelchair driving. *Computational Intelligence and Neuroscience*, 2007:Article ID 25130, 2007.

[3] W. G. Walter, R. Cooper, V. J. Aldridge, W. C. McCallum, and A. L. Winter. Contingent negative variation: an electric sign of sensorimotor association and expectancy in the human brain. *Nature*, 203:380–4, 1964.

[4] L. Bozinovska, S. Bozinovski, and G. Stojanov. Electroexpectogram: Experimental design and algorithms. In *Proceedings IEEE Biomedical Engineering Days, 1992*, pages 58–60, 1992.

[5] P. Kropp, A. Kiewitt, H. Göbel, P. Vetter, and W. D. Gerber. Reliability and stability of contingent negative variation. *Appl Psychophysiol Biofeedback*, 25:33–41, 2000.

[6] B. Rockstroh, T. Elbert, A. Canavan, W. Lutzenberger, and N. Birbaumer. *Slow Cortical Potentials and Behaviour*. Urban and Schwarzenberg, 2nd edition, 1989.

[7] C. M. Bishop. *Pattern Recognition and Machine Learning*. Springer, 2006.

[8] C. J. C. Burges. A tutorial on support vector machines for pattern recognition. *Data Mining and Knowledge Discovery*, 2:121–167, 1998.