Single trial detection of spatial covert visual attention for BCI

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Abstract

This paper discusses a time-dependent classification approach for single trial recognition of spatial covert visual attention for Brain–Computer Interface. Covert visual attention is a natural and intuitive mental task that does not require any external stimulation. The possibility to recognize it from single trials is essential for a future online close-loop BCI. Experimental results indicate the feasibility of the proposed approach and its high performance in an offline study. We achieved an accuracy of 84.1±8.9 % with a rejection of 6.5±6.6 % averaged across subjects.

1 Introduction

Some Brain–Computer Interface (BCI) paradigms rely on human visual processes to elicit specific patterns in the brain (i.e. P300, RSVP, SSVEP). In general, these paradigms require external stimulation and even overt attention whereby the user must gaze at the desired target. A much more natural, flexible and truly "brain" approach is to exploit voluntary covert visual attention that does not require any stimulation nor gazing.

Different neurophysiological studies have demonstrated the involvement of α-band in visual attention tasks [1, 2, 3, 4]. The synchronization of the alpha band in the parieto-occipital regions seems to reflect an ipsilateral inhibition mechanism in the retinotopical spatial organization of the visual cortex [3]. Some works have shown the possibility to discriminate the spatial focus of covert visual attention on grand averages [5]. However, attempts to recognize it from single trials are rare [6, 7, 8] although essential for a future online closed-loop BCI based on covert visual attention. In this work, we propose a time-dependent classification approach for single trial recognition of covert visual attention and report its high performance on an offline study with three subjects.

2 Methods

Three healthy volunteers (age 28±2.5 years) participated in this experiment. All subjects reported normal or corrected-to-normal vision. Subjects didn't have any previous experience with spatial covert visual attention paradigms.

2.1 Visual paradigm and task

In this study we focus on a two-class visual attention task. A white cross in the middle of screen and two target positions were displayed (white circles at a radius of 15°, position bottom left and bottom right). Subjects were instructed to gaze continuously at the white cross and focus their attention on one of the two targets according to the symbolic green cue (size 3.12°) appearing at the beginning of the trial. After 3000–5000 ms at the end of the attention period, a red circle appears at the correct target location. Figure 1 shows the schematic representation of the protocol with the time intervals adopted.

Each subject performed a total of 200 trials in 5 different runs along the same session day. Equal number of stimuli for both classes were presented.

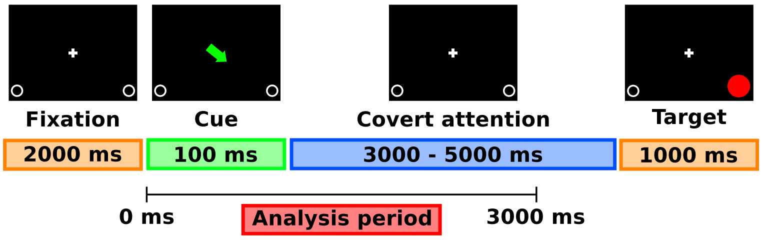

Figure 1: The visual attention protocol. The fixation period starts 2000 ms before the cue. The cue (100 ms duration) indicated the side where to focus attention. After 3000–5000 ms the circle corresponding to the correct target location becomes red (for 1000 ms). In the figure, the red circle is much larger than in reality for visualization purposes.

2.2 Data acquisition and processing

Signals were recorded with a 64-channel Electroencephalogram (EEG) system at 2048 Hz sampling rate. In parallel Electrooculogram (EOG) was recorded by means of 3 additional electrodes, two placed sideways to the eyes and one in the middle of the front. EEG was filtered (Butterworth filter, order 3, cut-off frequencies 5–35 Hz) and downsampled to 512 Hz. Afterwards, we applied a Laplacian spatial filter based on 8 neighbors (if possible).

We computed continuous wavelet transformation (complex Morlet family) on the data. The frequency range has been limited to 8–24 Hz. The mother wavelet has been selected in order to highlight the contribution in the α-band. This selection ensured a minimum frequency resolution of 2.65 Hz (at 24 Hz) and a minimum time resolution of 90 ms (at 10 Hz). Baseline has been computed trial by trial (baseline interval 300 ms before the cue) and has been subtracted to the trial period.

Vertical and horizontal eye movements were computed with a bipolar derivation of the EOG electrodes in the frequency range of 1–7 Hz. We discarded trials where any of the two EOG components had an amplitude higher than 30 μV. This value was selected by visual inspection. The average number of discarded trials across subjects was $8.3 \pm 3.6\%$.

2.3 Features analysis

The first part of this work has been devoted to study the separability of the features distributions over time during the trial. The wavelet transformation allows us to see clearly this evolution for each pair frequency-channel (defined as feature). Based on neurophysiologycal evidences, we preselected the features coming from the parieto-occipital regions of the brain. We performed the analysis until 3000 ms after the cue in order to avoid target–related bias (see Figure 1). We divided each trial in 10 non-overlapping windows (length of each window 312.5 ms) in order to understand the evolution of the features over time. In each window, we computed the Fisher's score of each feature. This way, we obtained the most discriminable features for each time interval.

In addition, we have estimated a confidence level for each window. This value reflects how much we can trust the features in a given time interval. This confidence level has be computed by normalizing (window by window) the sum of the Fisher's score values of the selected features with respect to the minimum and maximum of the trial.

2.4 Time-dependent classification

In this section, we describe the classification method used in order to recognize the visual attention task on single trials. The analysis performed gave us the possibility to select different features according to the time interval. For each time window, we trained and tested a QDA classifier with the most discriminable features. In addition, for each time window t, we transformed the output of the corresponding QDA classifier into a posterior probability by using as prior the posterior at time

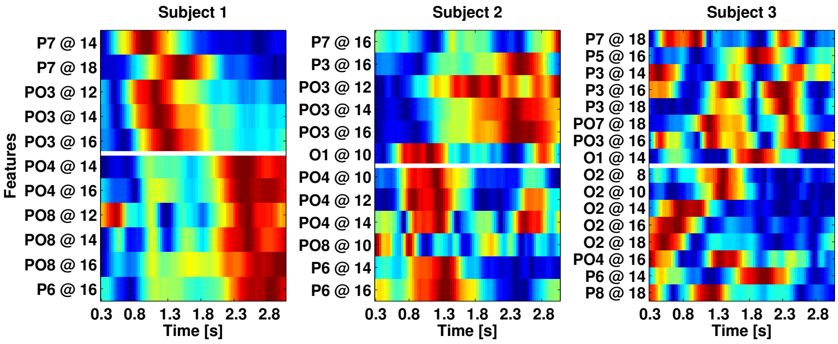

Figure 2: Evolution over time of the most discriminant features selected individually in each time window. The values have been normalized between 0 (blue) and 1 (red). The horizontal line represents the division between left and right hemisphere (top and bottom part, respectively).

$t-1$. Furthermore, we accumulated evidence over time by combining the posterior probabilities by means of the following expression:

$$p(y_t) = \alpha(t) \times p(y_t|x_t) + (1 - \alpha(t)) \times p(y_{t-1}) \tag{1}$$

where $p(y_t|x_t)$ is the posterior probability, $p(y_{t-1})$ the evidence accumulated up to time $t-1$ and $\alpha(t)$ an integration parameter corresponding to the confidence level of each window (see section 2.3). Afterwards, we integrated $p(y)$ over the whole time period (0–3000 ms) to make the decision (left, right or rejected) at the end of the trial. The rejection threshold was fixed to 0.8 for all subjects. We tested our method with 10-fold cross validation and averaged the performances.

3 Results

In this section, we first describe the outcomes of our feature analysis and motivate the time-dependent classification approach introduced before. In the second part, we present the classification results of this method.

Figure 2 shows the evolution over time of the features with the highest Fisher's score values. These features were individually selected in each time window. The first clear result is that they are not consistent across subjects. Nevertheless, we can see that subjects 1 and 2 have a spatial consistency with respect to the brain regions (horizontal white line in the figure). For subject 1, the left region of the brain is more discriminable in the first part of the trial, while in the second part, the right region assures more separability between the two classes. Features of subject 2 present a specular behaviour. However, for subject 3 we cannot identify a clear spatial consistency.

The investigation on the separability of the features over time yields some preliminary conclusions. First of all, the time intervals with high discriminability are not stable across subjects. Second, for each subject it's not possible to identify features that guarantee high separability during the whole trial. It is for this reason that we decided to train individual classifiers for each time window, each with the most discriminant features of that window (see section 2.4).

This time-dependent approach reaches high classification performances on single trial for all subjects. Table 1 shows the total number of correct, wrong and rejected trials for each subject across the whole dataset. In addition, last two columns report the accuracy performances computed on the accepted trials and the rejection rate across 10-fold cross validation.

The best classification rate is for subject 1 (89.4 ± 7.9 %). The result is in line with the features map showed in Figure 2. In fact, the separability of the selected features is more consistent over time for this subject compared to the others. Nevertheless, the time-dependent feature selection and classification assures high performances also in case of subject 3 where the evolution in time of the discriminability between the two classes cannot be well defined.

Table 1: Results of the 10-fold cross validation study. Total number of correct, wrong and rejected trials across the whole dataset, as well as accuracy and rejection performances.

Subject	# Correct	# Wrong	# Rejected	Accuracy	Rejection
1	157	19	8	89.4±7.9 %	4.4±5.6 %
2	131	34	21	79.5±8.6 %	11.2±6.9 %
3	141	28	5	83.4±8.1 %	2.8±3.9 %

4 Conclusion

In this work we propose and demonstrate a time-dependent classification approach for single trial recognition of covert visual attention. The motivation for such an approach is that, based on our findings, it seems not to be possible to identify features with high discriminability that people can sustain over time. This result is supported by recent neurophysiological studies on time modulation of α-power during spatial visual attention [4]. Experimental results with three subjects indicate the feasibility of the approach in an offline study where grand average performance is 84.1±8.9 %. Interestingly, our approach is a powerful mixture of neurophysiological findings and data-driven analysis. The former guide the selection of the parieto-occipital cortical regions and the frequency bands. The latter helps in exploiting natural fluctuations in the discriminant features so as to avoid any assumption about time intervals where to carry out classification.

The next challenges are twofold: to demonstrate this covert visual attention BCI in a closed-loop experiment and to show the stability of the selected features across different sessions (days).

Acknowledgements

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