Towards a single trial detection of spatial covert visual attention for BCI

L. Tonin, R. Leeb, J. del R. Millán
Chair in Non-Invasive Brain-Machine Interface, 
Ecole Polytechnique Fédérale de Lausanne 
Lausanne, Switzerland 
luca.tonin@epfl.ch

Abstract
This paper discusses a time-dependent classification approach for single trial recognition of spatial covert visual attention for Brain–Computer Interface (BCI). 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 show the feasibility of the proposed approach and its high performance on an offline study.

1 Introduction
Some Brain–Computer Interface (BCI) paradigms rely on human visual processes to elicit specific patterns in the brain. 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.

Many neurophysiological studies have demonstrated the involvement of α-band in visual attention tasks [1, 2]. The synchronization of the alpha band in the parieto-occipital regions seems to reflect an ipsolateral inhibition mechanism in the retinotopical spatial organization of the visual cortex. Some works have shown the possibility to discriminate the spatial focus of covert visual attention on grand averages [3]. However, attempts to recognize it from single trials are rare [4, 5] but are 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 show 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 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 appearing at the beginning
of the trial. After 3000–5000 ms, 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.

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 downsamped to 512 Hz. Afterwards, we applied a Laplacian spatial filter.

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 \( \alpha \)-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 have been detected automatically. The two components (vertical and horizontal) have been computed with a bipolar derivation of the EOG electrodes. We discarded trials where any of the two EOG components has an amplitude higher then a given threshold (mean of trials discarded across subjects 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 neurophysiological evidences, we preselected the features coming from the parieto-occipital regions of the brain. 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 $t - 1$. Furthermore, we accumulated evidence over time by combining the posterior probabilities by means of the following expression:

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

(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 trial to make the final decision. 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 results for the three subjects separately for each class.
Table 1: Classification performances for each class (mean and standard deviation across 10 folds).

<table>
<thead>
<tr>
<th>Subject</th>
<th>Accuracy Right</th>
<th>Accuracy Left</th>
<th>Rejection Threshold</th>
<th>Rejection Right</th>
<th>Rejection Left</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>92±7%</td>
<td>86±8%</td>
<td>0.8</td>
<td>18±6%</td>
<td>15±4%</td>
</tr>
<tr>
<td>2</td>
<td>81±7%</td>
<td>72±13%</td>
<td>0.7</td>
<td>7±4%</td>
<td>13±7%</td>
</tr>
<tr>
<td>3</td>
<td>77±8%</td>
<td>82±6%</td>
<td>0.7</td>
<td>16±7%</td>
<td>14±7%</td>
</tr>
</tbody>
</table>

The best classification rate is for subject 1 (89±8%, average across classes). 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.

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 [6]. Experimental results with three subjects show the feasibility of the approach in an offline study where grand average performance is 81.7%. 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

This work is supported by the European ICT Programme Project TOBI FP7-224631.

References


