

# Which Physiological Components are More Suitable for Visual ERP Based Brain–Computer Interface? A Preliminary MEG/EEG Study

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**Abstract** We investigated which evoked response component occurring in the first 800 ms after stimulus presentation was most suitable to be used in a classical P300-based brain–computer interface speller protocol. Data was acquired from 275 Magnetoencephalographic sensors in two subjects and from 61 Electroencephalographic sensors in four. To better characterize the evoked physiological responses and minimize the effect of response overlap, a 1000 ms Inter Stimulus Interval was preferred to the short (<400 ms) trial length traditionally used in this class of BCIs. To investigate which scalp regions conveyed information suitable for BCI, a stepwise linear discriminant analysis classifier was used. The method iteratively analyzed

each individual sensor and determined its performance indicators. These were then plotted on a 2-D topographic head map. Preliminary results for both EEG and MEG data suggest that components other than the P300 maximally represented in the occipital region, could be successfully used to improve classification accuracy and finally drive this class of BCIs.

**Keywords** Brain–computer interface · P300 · MEG · EEG · SWLDA

## Introduction

Brain–computer interface (BCI) systems represent a means of communication for individuals who experience impairment in expressing their intents to the external world and so a way to reduce the impact of disability caused by diseases such as multiple sclerosis, trauma, stroke (Wolpaw et al. 2002). A BCI translates brain signals measured from the subject into features suitable for driving an external device such as a speller, a wheelchair, or a robotic arm.

A visual P300-based BCI exploits the P300 response, which can be recorded on the electroencephalogram (EEG) in response to rarely occurring events embedded in a set of frequent events with different physical properties. These events are usually represented by tone pitches or images. If attention is focused on the rare event, a time and phase-locked response of positive polarity—the P300—is evoked in the EEG approximately 300 ms after its presentation. By detecting the events responsible for the P300, we can infer the intent that the subject wishes to communicate.

One of the most frequently used P300-based BCI system relies on a speller represented by a matrix of symbols displayed on a computer screen (Donchin et al. 2000). By

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focussing on specific elements of the matrix, the user can achieve a simple but effective communication. Optimization of this kind of BCI systems has received increasing attention in recent years (Sellers et al. 2006; Serby et al. 2005; Nijboer et al. 2008; Allison and Pineda 2006; Krusienski et al. 2008). In these studies the inter stimulus interval (ISI) is usually set in the 175–350 ms range, which implies that a stimulation occurs before the previous response has extinguished. Whilst this choice has obvious communication speed advantages, it might hide some aspects related to the physiological response. A recent study has also addressed the issue of the “best electrodes set” to be used, analyzing a limited number of sensor configurations (Krusienski et al. 2008). In this study, we used a classical P300-evoking speller to investigate whether any evoked component, besides the P300, could be used to improve the classification accuracy and, more in general, to evaluate its topographic distribution. We used two electrophysiological modalities—EEG and magnetoencephalography (MEG)—to investigate the potential advantage of the higher spatial resolution and signal to noise ratio of MEG with respect to the traditionally used EEG.

## Material and Methods

Six subjects participated in the study and two different recording techniques were used: EEG (four subjects, three female, one male, mean  $\pm$  SD = age  $30.25 \pm 10.04$ ) and MEG (2 male subjects aged 51, 42). MEG was chosen for this BCI protocol because of its higher spatial resolution (Mellinger et al. 2007), offering more precise information about the brain areas involved in the discrimination task, whilst EEG retains a competitive advantage in terms of cost and accessibility. We used a widely applied P300

protocol in BCI research (Donchin et al. 2000) based on a speller constituted by a square matrix of 36 symbols.

In line with the majority of visual P300 protocols, subjects were asked to fixate a specific letter and count the number of times it flashed. Each row and column flashed 15 times with a 1000 ms inter-stimulus interval with a 100 ms duration. We chose a longer ISI with respect to previous studies in order to minimize responses overlap.

The rows and columns which do not contain the selected character were defined as non-targets. Twelve different classes of responses—one for each row and column—were separately averaged off-line. A classifier was employed to identify the two target responses (one row, one column). The attended character was identified as the one located at the intersection of the target row and the target column.

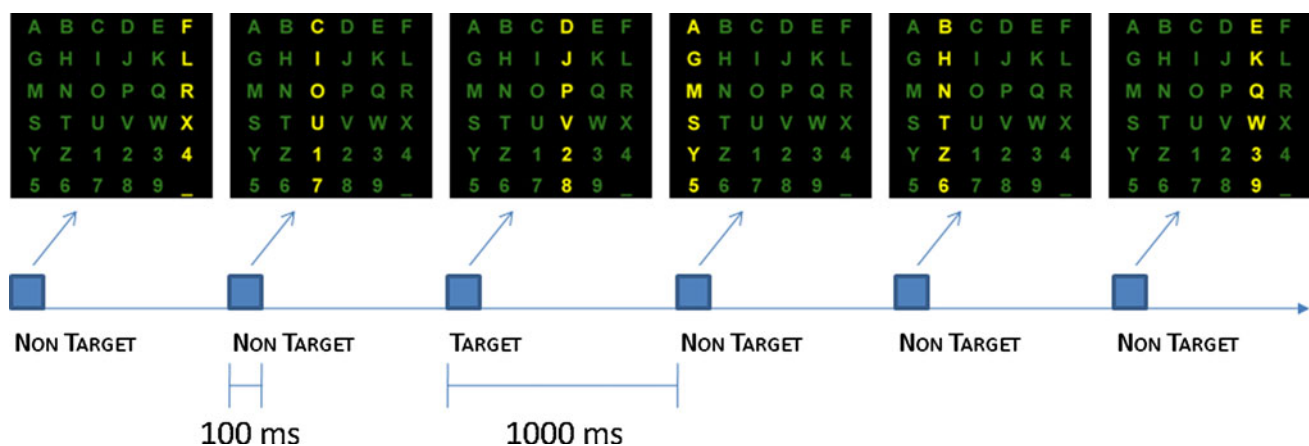
In Fig. 1 a short stimulation segment in which the requested letter is placed in the fourth column is reported. The corresponding sequence of target and non-target stimuli is shown just below the time axis.

In the EEG experiment, each subject was presented with all the 36 letters, for a total of 6,480 stimuli (1,080 targets, 5,400 non-targets), while for the MEG subjects had to concentrate on 18 letters for a total of 3,240 stimuli (540 targets, 2,700 non-targets) each.

In both cases, data were converted to the NPX file format (Bianchi et al. 2007) and then processed with the NPXLab Suite (available at <http://www.braininterface.com>).

## Data Acquisition

MEG was recorded in a magnetically shielded room using a system (VSM Medtech Ltd, Port Coquitlam, BC, Canada) comprising 275 gradiometers. Data was sampled at 600 Hz simultaneously with trigger signals generated by specifically designed stimulation software running on a separate PC.



**Fig. 1** An example of stimulating sequence (by columns). Every 1000 ms all the letters of one of the six columns turn from *green* to *light yellow* for about 100 ms. This evokes a physiological response if the subject is watching an intensified letter

EEG was recorded in a silent room using an EBNeuro Mizar system (Florence, Italy) from 61 sensors, with a sampling rate of 256 Hz. Reference electrode was positioned between AFz and Fz while ground was between Pz and POz.

### Data Processing

Acquired data was band-pass filtered (0.5–30.0 Hz). MEG signals were downsampled to 150 Hz.

A stepwise linear discriminant analysis (SWLDA) classifier (Krusienski et al. 2008) was used. It was implemented using the C++ programming language and included in the Body Language Framework (Bianchi et al. 2003) (BF++). The NPXLab suite, a main component of the BF++, was then used for the evaluation of the performances of the classifier. A screenshot of the classifier option form is shown in Fig. 2.

The classifier was fed with data relative to the first 800 ms of the signal after the visual stimulations for each sensor, iterated over the whole sensors set. This allowed preservation of topographic information regarding the ability of the classifier to recognize the correct targets.

For all of the six subjects the classifier was trained by using nine of the asked alphanumeric characters, while the classification was performed on the remaining ones. This procedure was automatically iterated, each time randomly choosing a new set of training characters and using the

remaining ones for the testing, until 1,080 classifications per sensor were performed.

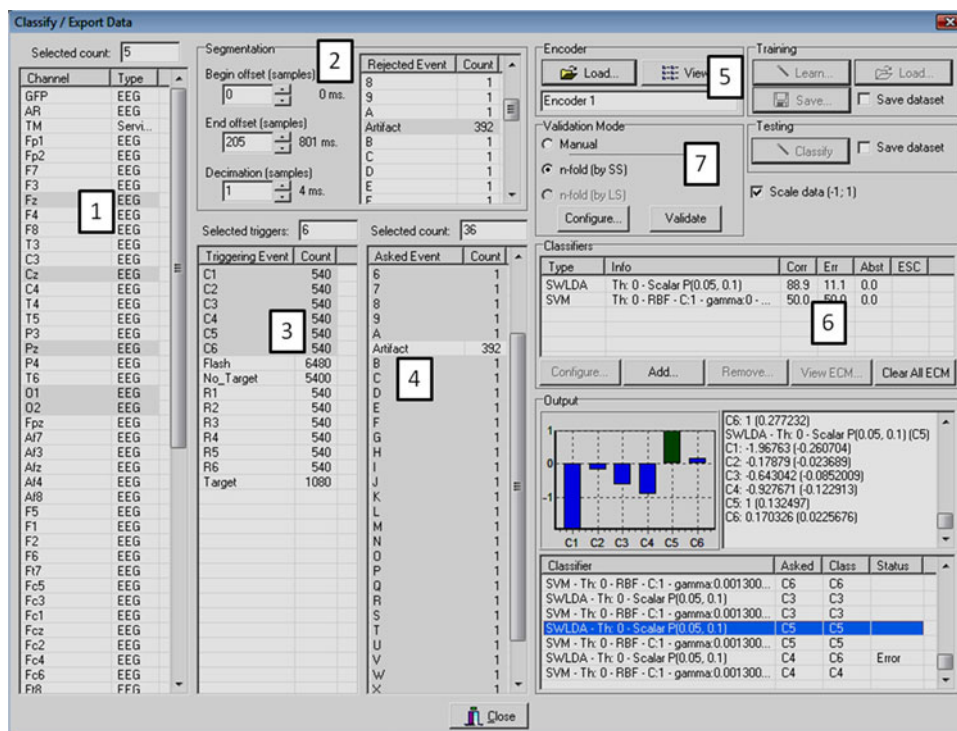
For each sensor, the amounts of correct, wrong and uncertain (the classifier abstained from decision) classifications were computed and the percentage of the correct ones was represented on a 2-D topographic map using a quadratic interpolation on the eight nearest neighbors to avoid any spatial filtering effect at sensors locations.

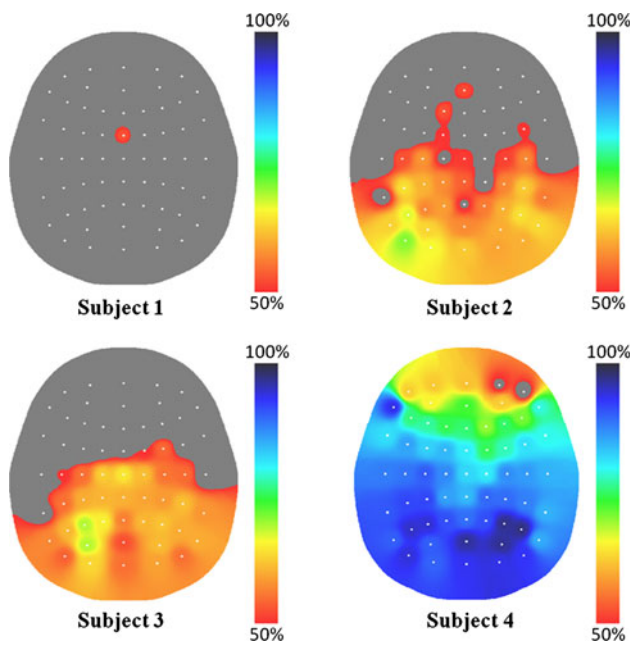
### Results

Maps relative to the percentage of correct classifications and relative to the four EEG and the two MEG subjects, respectively are reported in Figs. 3 and 4. Values below 50% are reported in gray (chance level was 16.66%) otherwise they are mapped through a color scale, ranging from red, corresponding to the threshold value, to blue, corresponding to the perfect (100%) accuracy. White dots represent sensors positions. From the EEG maps (Fig. 3) it can be easily seen that, except for Subject 1, who confessed lack of attention for all the duration of the protocol, a wide brain area covering either the central or the occipital region provides accuracies above the threshold. The best sensor locations were respectively FCz (with an accuracy of 52.4%), PO7 (70.3%), PO3 (68.3%) and P6 (92.2%).

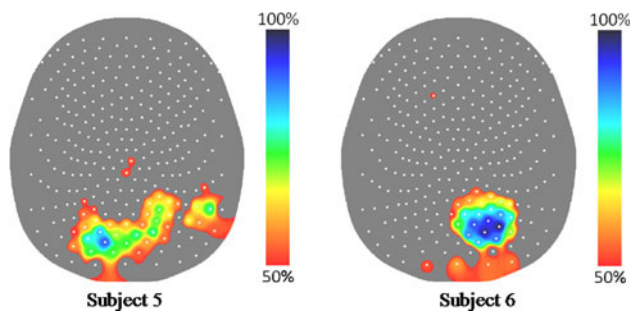
The corresponding maps relative to MEG data are reported in Fig. 4. In this case the brain areas that provide

**Fig. 2** The main classifiers form. One can: (1) select the sensors to use (left list), (2) set the segmentation parameters, (3) select the triggering events to use, (4) select the asked characters to use, (5) select the encoder, from which target and non-target triggers are automatically computed. The Classifiers group box (6) shows the actually selected classifiers and allows configuring them. (7) Validation can then be manual or automated (folded)





**Fig. 3** Subjects 1–4, EEG single sensors classification maps. Values are expressed in percentage



**Fig. 4** Subjects 5–6, MEG single sensors classification maps. Values are expressed in percentage

the best accuracies are more focused and localized in the parieto-occipital region. The best performance (90.4%) was obtained at a left occipital sensors, location MLO31 for subject 5 and 98.33% at location MRO21 for subject 6.

In addition, in order to quantify and point out the different contributors due to the visual N100 and the cognitive P300 components, for subject 4 classifications were performed both with the 0–250 ms interval after the stimulations, in which the N100 is most prominent, and with the 250–500 ms interval, in which is the P300 to be the most prominent. Subject 4 was chosen because he showed a high activation of the occipital zone, with the classification maps in the 0–800 ms interval (Fig. 3), and an ample N100 component from an event related potentials (ERP) analysis. In Fig. 5 averages of the target (blue lines) and non-target (orange lines) trials over all the letters and computed for each electrode are shown. It is evident that, in the

0–250 ms interval, the N100 component is very predominant, with respect to the P300 component that is less ample in the 250–500 ms. The other subjects show a similar behavior, even if the P300 component may be larger. In any case, the N100 component is still present and clearly visible.

Finally, results of the classifications with the two intervals are shown in Fig. 6: it is evident that, classifying with the 0–250 ms interval, almost all the occipital electrodes show the highest accuracy (100%), while with the 250–500 ms interval, central electrodes activate the most, even if with lower accuracy (50–70%) with respect to the previous case. This confirms that earlier components in the occipital region play an important role in the classification process.

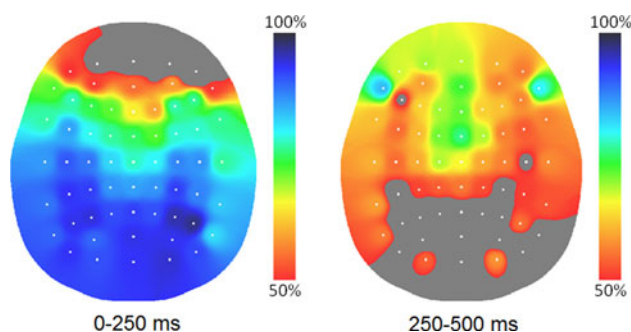
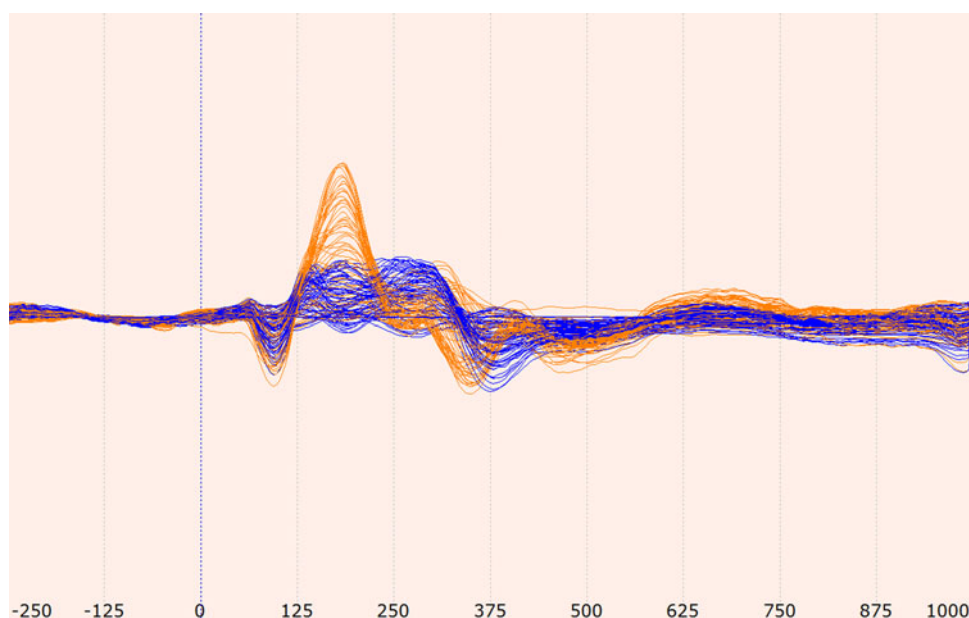
## Discussion and Conclusions

In this study a classical BCI speller protocol has been used to investigate the existence of other physiological components besides the P300 that could be used to increase the classification accuracy and to determine the brain areas in which they are located. In order to keep the responses to the stimulations separate, so avoiding destructive interferences among different overlapping evoked components, a longer ISI than the most used ones, was preferred in the experimental design.

Our preliminary results suggest that the sensors belonging to the occipital region of the brain should be included in the sensors set for this class of protocols. This finding is of particular importance given the rising interest in using only a limited set of sensors in BCIs for practical reasons. It should be mentioned that in one subject (subject 1) the classification accuracy was very poor. The same subject confessed later that had a certain difficulty to stay well concentrated and this can be the main reason. Moreover, it is well known that differences among subjects are usually observed in whatever BCI protocol so that the final performances of these systems might vary from user to user.

The topographic approach used in this experiment—using one sensor at a time for the classification and evaluating the classifier accuracy globally—is a promising data-reduction tool in identifying the brain regions in which the difference between target and non-target responses is maximal. Whilst simultaneous use of multiple sensors is known to provide best results for BCIs, the approach used in the present study allows the preservation of topographic information regarding the ability of the classifier to recognize the correct targets. This approach can be also useful in investigating the role of different brain areas in the discrimination task (target–non-target) typical of P300-based BCI protocols. In fact, mapping the

**Fig. 5** Average ERP for Subject 4: *orange lines* represent the target averages on all the electrodes (one line per electrode), while *blue lines* represent the corresponding non-target averages. The averages were computed using all of the letters



**Fig. 6** Classification maps for Subject 4, in the 0–250 ms (*left*) and 250–500 ms (*right*) time intervals

classification results could provide us with an indirect measure of brain processing load in the execution of this experimental protocol. In particular, given that the SWLDA classifier tries to maximize differences among a discrete set of features to discriminate classes of data, it will perform better whenever the differences are intrinsically high. One can then deduce that the better the performances of a classifier, the higher the differences among the classes and then of the physiological signals.

The involvement of the parieto-occipital region, as outlined in this experiment by both EEG and MEG data, also suggests that some visual evoked component (e.g. N100) should be used for BCIs in addition to the cognitive ones (P300) in order to improve the performances of current BCIs. This could be done by including specific sensors and/or early components of the physiological responses.

Finally, MEG data seems to be more focused, so that head misalignment among different sessions should be checked and eventually corrected if physiological signals are merged over time.

Reproducibility of these findings is currently under investigation by extending the sample for both the EEG and MEG measures.

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