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Influence of P300 latency jitter over (c)overt attention BCIs

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Abstract

Several ERP-based BCIs that can be controlled even without eye movements (covert attention) have been recently proposed. However, when compared to similar systems based on overt attention, they displayed a significantly lower accuracy. In the current interpretation, this is ascribed to the absence of the contribution of short-latency visual evoked potentials (VEPs) in the tasks performed in the covert attention modality. This study aims to investigate if this decrement (i) is fully explained by the lack of VEP contribution to the classification accuracy; (ii) correlates with lower temporal stability of the single-trial P300 potentials elicited in the covert attention modality. We evaluated the latency jitter of P300 evoked potentials in three BCI interfaces exploiting either overt or covert attention modalities in 20 healthy subjects. Results highlighted that the P300 jitter is higher when the BCI is controlled in covert attention and classification accuracy negatively correlates with jitter.

1 Introduction

The Farwell and Donchin's P300 Speller (1988) is among the most widely validated Brain Computer Interface (BCI) paradigms for communication applications. Brunner and colleagues (2010) have recently shown that the P300 Speller recognition accuracy was significantly decreased if the subject was not allowed to gaze at the target stimulus. Several user interfaces designed to be used in covert attention modality have been implemented and tested with the overall result of a lower system performance in covert with respect to overt attention usage. The observed superiority in the system performances under overt usage modality was mainly ascribed to the contribution of visual evoked potential (VEP) components recorded at occipital and parieto-occipital sites (Aloise et al., 2012; Treder and Blankertz, 2010). Another important contribution regards the P300 latency jitter that occurs when the lag between each target stimulus onset and the related potential peak is not constant for the different stimulus repetitions. Thompson and colleagues (2013) demonstrated that the accuracy

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achieved with the P300 Speller was strongly correlated with the jitter in the P300 latency. In this study we addressed the issue of whether the accuracy of BCIs used in covert attention modality i) is fully explained by the lack of VEP contribution to the classification accuracy and/or ii) is correlated with a lower stability of the P300 potential elicited in the covert attention with respect to the overt attention modality.

2 Materials and methods

Twenty healthy volunteers (14F and 6M, 28±5 years) were requested to complete a spelling task using a BCI. For this purpose, visual stimuli containing 36 alphanumeric characters for the GeoSpell (used in covert attention, Aloise et al., 2012) and the P300 Speller (Farwell and Donchin, 1988) interface (used in overt attention), and 2 characters for a simple Visual Oddball interface used in overt attention, were delivered in different arrangements, through three alternative visual interfaces. For all interfaces, the frequency of target stimuli was 16.7% (i.e. 1/6).

Scalp EEG signals were recorded (g.USBamp, gTec, Austria) from 8 Ag/AgCl electrodes (Fz, Cz, Pz, Oz, P3, P4, PO7 and PO8, referenced to the right earlobe and grounded to the left mastoid) at 256 Hz. Visual stimulation and acquisition were operated by means of the BCI2000 software. At the beginning of each trial the system suggested to the subject the character to be written before the stimulation started. Recordings took place in two sessions on separate days. Each session consisted of 3 runs for each interface and 6 trials (i.e. characters) per run. Subjects were required to spell 6 words (3 words per session) using both the GeoSpell and the P300 Speller interfaces; subjects were required to spell the sequence “OOOOOO” (all ‘rare’ stimuli) using the Visual Oddball interface. This latter sequence was repeated for six runs. Each trial consisted of 8 stimulation sequences and corresponded to the selection of a single character displayed on the interface. Each character was intensified for 125ms (Stimulus duration), with an Inter Stimulus Interval (ISI) of 125ms.

The EEG signals were segmented into 800 ms overlapping epochs following the onset of each stimulus. Two runs of each recording session were considered as training set while the remaining run provided the data for the testing set, exploring all possible permutations.

P300 latency jitter evaluation: To evaluate the influence of the P300 latency jitter on the classification accuracy, it was necessary to reconstruct the P300 potential waveform for each single epoch. In this regard, we applied a method based on the Continuous Wavelet Transform (CWT) and the estimation of the empirical Cumulative Distribution Function (CDF), in order to enhance the signal (P300) to noise (spontaneous EEG) ratio (Aricò et al, 2014). At this point, we calculated the inverse CWT for each epoch, and we estimated the latency of the P300 potential as the highest peak of the signal into the epoch. The latter had been manually selected from the averaged waveforms, to embrace the whole P300 shape. We quantified the jitter of the P300 latency as the difference between the 3rd and the 1st quartile of each distribution for each testing run. These analyses were performed on the Cz channel, where the P300 is most prominent.

BCI accuracy evaluation: For each participant, we assessed the BCI accuracies offline, as a function of the number of stimulation sequences averaged during each trial. We used a Stepwise Linear Discriminant Analysis (SWLDA, Aloise et al., 2012) to select the most relevant features that allowed to discriminate between target and non-target stimuli. We performed a three-fold cross-validations exploring all possible combinations of training (2 runs) and testing (1 run) data set for each session and interface. We evaluated the performance of the subjects for each interface considering i) [*Whole epoch*] the entire time length of the epoch (0-800ms), ii) [*Whole epoch decimated*] same epoch length as above, reducing by a factor of 12 the number of time samples (each new sample is the average of 12 original samples), iii) [*P300 epoch non-realigned*] only the epoch segment containing the P300 potential thus disregarding those VEPs components influenced by

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gazing at the target stimuli, iv) [*P300 epoch realigned*] same epoch length as above, using potentials obtained after realignment of the single epochs, whose time courses were shifted according to the estimated P300 latency values.

Correlation between P300 latency jitter and performance: The information transfer rate (ITR, bit/min) was calculated at each fold of cross-validation as a function of the number of sequences in the trial. In particular, we calculated the mean value of the ITR along the 8 stimulation sequences, in order to have a synthetic measure of the system's performance. To assess the correlation between the ITR_{Mean} and the P300 latency jitter, we estimated the non-parametric Spearman's rank correlation coefficient between these variables.

3 Results

P300 latency jitter: Significant differences of P300 latency jitter elicited by the 3 interfaces were explored by means of one-way repeated measures ANOVAs (Confidence Interval = .95) where interface was considered as factor and the P300 latency jitter as dependent variables. The analysis revealed a significant difference across the interfaces for the jitter ($F(2, 357)=52.58$; $p=9x10^{-6}$). Post-hoc analysis (Duncan test) showed that the GeoSpell produced a latency jitter significantly larger than the P300 Speller and the Visual Oddball (mean: 108±24ms, 76±24ms, and 74±38ms, respectively; $p<10^{-4}$).

BCI accuracy: Differences in the classification accuracy achieved with each of the 3 visual interfaces and each of the 4 conditions introduced previously (Figure 1a). A two-way repeated measures ANOVA (Confidence Interval = .95) was performed with interfaces and conditions as factors and the accuracy per stimulation sequences as dependent variables. The analysis revealed a significant interaction between the factors ($F(6, 1428)=42.57$; $p=10^{-9}$). The Duncan's multiple range test was used for post hoc comparison. The differences in the epoch choices and the interfaces are summarized in Figure 1b.

Correlation between P300 latency jitter and performance: The non-parametric Spearman's rank correlation coefficient was used to evaluate the correlation between the classification accuracy as expressed by the ITR_{Mean} values and the P300 latency jitter obtained for each interface. We found a significant negative correlation between the latency jitter and the accuracy achieved by the subjects with all 3 interfaces (GeoSpell: r=.17 p=.04; P300 Speller: r=.35 $p=10^{-4}$; Visual Oddball: r=.18 p=.03). Considering all the interface together, we found a significant negative correlation as well (r=.50 $p=2x10^{-23}$).

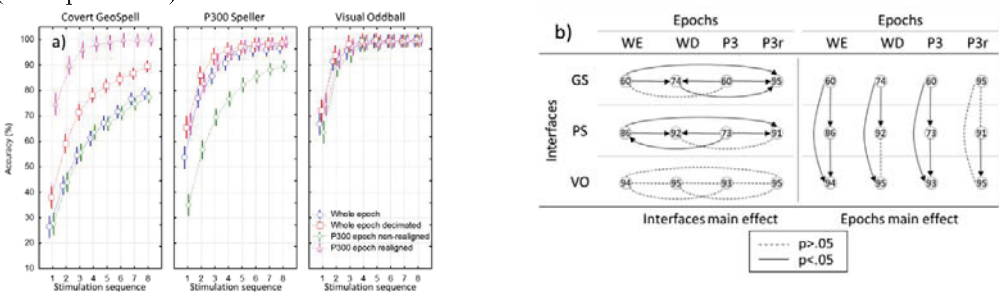

Figure 1: (a) Mean and confidence intervals (CI = 0.95) of the cross-validation target classification accuracies achieved with the three interfaces, relative to each epoch choice as a function of the number of stimulations; (b) Graphical representation of the differences between the epochs (WE: Whole epoch; WD: Whole epoch decimated; P3: P300 epoch non-realigned; P3r: P300 epoch realigned) and the interfaces (GS: GeoSpell; PS: P300 Speller; VO: Visual Oddball) in terms of accuracy, highlighted by the post hoc test. Numbers in the circles indicate the percent mean accuracy value.

4 Discussion

The overall aim of this study was to investigate the influence of the P300 latency jitter evoked during (c)overt attention based BCI tasks on the accuracy achieved. The results proved that when the user operates a BCI using covert attention, the latency jitter is greater than using overt attention. Particularly, the P300 latency jitter was significantly greater when using the GeoSpell interface than using the other interfaces. In line with previous studies (Brunner et al., 2010), our findings on the first phenomenon clearly indicate the significant contribution of the early VEPs to the classification accuracy only for the overt (i.e. P300 Speller) interface. Also, removing the VEP contribution from ERPs elicited using the P300 Speller and the GeoSpell interface, the latter still performed significantly worse than the former, suggesting that the lack of VEPs is not the only reason for the performance decrement in the tasks performed in covert attention modality. In addition, a significant correlation was found between the latency jitter and the BCI performances for all the interfaces.

5 Conclusion

We found that (i) even canceling the contribution of short latency VEPs, the P300 Speller interface (used in overt attention modality) remains more accurate than the GeoSpell (used in covert attention); (ii) the P300 latency jitter is negatively correlated with the accuracy of the BCI classifier; (iii) a compensation of the P300 latency jitter makes the GeoSpell (used in covert attention) than the P300 Speller.

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