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A virtuous BCI loop: adaptive decision making improves P300-spelling in two ways

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Abstract

A major challenge in Brain-Computer Interfaces (BCI) is the optimization of performance, regardless of the within and between user variability. A promising option is to move towards adaptive BCI that can accommodate fluctuations over time and subjects. An obvious criterion to be optimized is the speed-accuracy trade-off. We implemented a BCI whose decision speed or reaction time depends on the reliability of accumulated evidence. We instantiated a probabilistic classifier whose outcome can be up-dated online based on new incoming information. An entropic measure then enables us to derive an optimal stopping strategy, in a user-dependent fashion. We evaluated the proposed approach on 11 participants, during online P300-Spelling. We thus quantified the beneficial effect of this method. Importantly, we show that the adaptive mode creates a virtuous circle such that: the higher the spelling accuracy, the more the participant engages in the task and, in return, the higher the motivation the higher the BCI performance.

1 Introduction

A central question in BCI is how fast the system can produce a reliable command. Although BCI performances are often evaluated and reported using measures of bit rate, this one is rarely explicitly maximized online by the system. The vast majority of P300-Speller studies do fix the time for spelling a letter in a way that is supposed to optimize speed given some expected level of accuracy. Yet it is clear that the same strategy might not be optimal for every individual, at any time. In a given subject, adaptation would consist of varying the number of flashes per trial, given some measures of the user's level of engagement. Such a system should stop earlier whenever the user is very well focused on the task, and it would keep acquiring data whenever the user is unfocused and produces ambiguous signals. Hence for a given averaged trial duration, we expect an increase in accuracy with the adaptive approach compared to the traditional one. Moreover, in the case of BCI, such an adaptive approach might also trigger up the user's motivation. If so, we expect the online results to reflect not only the improvement due to the adaptive method but also some further positive effect due to the ensuing boost in motivation. This issue of optimizing the stopping criterion has already been addressed in a couple of studies relying on different measures of how robust is the decision about to be made (Serby et al. 2005; Jin et al. 2011). Remarkably though, the authors used a still fairly rigid approach instead of a fully flexible one. Their approaches were restricted to stop acquiring new observations after some varying amount of repetitions (blocks), rather than considering the possibility of deciding after an arbitrary amount of flashes (trials). As a consequence, the machine's reaction time can only take a few discrete values. Our approach proposes an information theoretic and probabilistic criterion, which enables us to generalize this optimal strategy, by allowing the machine to stop at any time during the evidence accumulation process.

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2 Method

2.1 Data acquisition

Eleven healthy subjects took part in this study (4 men, mean age = 26.9±6.4 (SD), range 19-40). They all signed an informed consent approved by the local Ethical Committee. We used a traditional 6x6 matrix made of letters (A-Z), digits (1-9) and an additional symbol for blanks (_). Pseudo-random groups of letters (adapted from Townsend et al, 2010) were flashed alternatively for 80ms, while the SOA was set to 150ms. The whole experiment included one training followed by three test sessions. The former consisted of 15 characters spelled with 10 repetitions and each test session was made of 20 5-letter words. Target letters were defined prior to the experiment and indicated to the subject by a green circle. Subjects were instructed to visually fixate the target and count how many times it was flashed.

We here report the online and offline comparison between two experimental conditions, which differed in the way the decision was made: one used a time-based decision (called the fixed condition) and the other involved an accuracy-based decision (called the adaptive condition). In the fixed condition, each trial consisted of 60 flashes (5 repetitions). In the adaptive condition, there was a maximum of 180 flashes by item (15 repetitions), but the actual number of flashes varied from one trial to the next, depending on the pre-determined threshold and the entropy of the current posterior probability distribution. The threshold was determined from each individual training set so that the average number of flashes equalled roughly 60 (5 repetitions). Participants spelled 4 blocks of five 5-letter words per condition and conditions were presented pseudo-randomly over time. The experiment lasted about an hour in total for each subject.

EEG data were recorded from 9 electrodes (Pz, P7, P8, P3, P4, PO9, PO10, O1, O2) following the extended 10-20 system and referenced to the nose. Data were digitized at 1000 Hz, band-pass filtered between 1 and 20 Hz and down-sampled at 100 Hz.

2.2 Feature extraction, classification and decision

Feature extraction consisted in a linear spatial filtering named xDAWN (Rivet et al., 2009). For classification, we used a simple probabilistic generative model of the data, based on a two multivariate-Gaussian mixture, further assuming conditional independence between features, over time and space (Naïve Bayes hypothesis). Importantly, we here extended our model to compute the posterior probability associated with each item of the matrix in a Markovian fashion; that is by applying Bayes rule after each new flash and considering the posterior belief as the prior for the next observation. After each flash, this method enables us to compute and update each letter's probability of being the target. Based on these up-dates, the adaptive decision relies on a natural information theoretic measure of uncertainty, the Shannon's entropy of the posterior distribution. Entropy decreases as information is accumulated, *i.e.* as the posterior distribution gets closer to an ideal distribution with full probability mass associated with a single item, meaning that the machine is sure about the target location. In the adaptive condition, a decision is made as soon as the entropy falls below the individually chosen threshold. By default, if the threshold is never met, a decision is made after fifteen repetitions.

2.3 Evaluation metrics and statistical tests

In order to compare the above described methods and conditions, we used two well-known measures of performance: spelling accuracy and bit rate (in bits/minute) as defined in (Wolpaw et al., 2000). To assess the statistical significance of differences in performance, we compared spelling accuracies, averaged numbers of flashes and bit rates using Wilcoxon tests.

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In order to evaluate a putative additional effect of motivation in the adaptive condition, we reprocessed some of the data offline in order to compare the two conditions based on the same fixed number of observations (24 flashes, i.e. 2 repetitions).

3 Results

In the fixed condition, the online spelling accuracy was 71% ± 16 (SD), which corresponds to 18.8 bits/minute. In the adaptive condition, it was 80% ± 14 (SD), for an average of 57 ± 4 (SD) flashes, which corresponds to 24.1 bits/minute. (Figure 1.A).

Wilcoxon tests revealed that both the spelling accuracy and the bit rate are significantly higher in the adaptive condition compared to the fixed condition ($p<0.01$ for both tests). Importantly, the number of flashes was not significantly different between the two conditions ($p=0.1$), it was even slightly lower in the adaptive condition.

To evaluate the effect of motivation, data from both conditions were reanalyzed offline, using the same time-based stopping criterion: a decision was made after the 24 first flashes. The obtained spelling accuracy proved significantly higher in the adaptive than in the fixed condition ($p<0.01$) (Figure 1.B). Since the number of observations was the same for both conditions, the ensuing bit rate proved also significantly higher in that same condition ($p<0.01$).

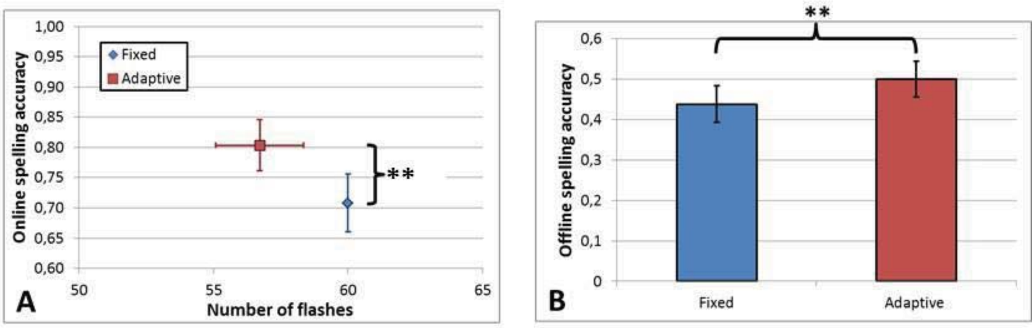

Figure 1. A/ Online spelling accuracy as a function of the averaged number of flashes for each condition: fixed (blue diamond), adaptive (red square). Error bars indicate the standard error of the mean. B/ Offline spelling accuracies obtained with the same datasets reanalyzed using a time-based criterion (decision made after 24 flashes). P-value: ** $p<0.01$.

4 Discussion

In this P300-Speller study, we first developed a new classification approach which up-dates the belief of the machine about target location, after each single electrophysiological observation. This single-trial based classification enabled us to propose and evaluate an adaptive decision making, which consist of implementing an optimal reaction time strategy in the machine, allowing for short spelling when the first few incoming pieces of evidence are strong enough and vice versa.

Adaptive decision making was proposed to overcome the limitation of the traditional time-based decision criterion used in the P300-speller and BCI in general. Indeed, a machine's adaptive decision, based on some information or accuracy criterion, allows for an optimal stopping strategy. In other words, the reaction time of the machine can be optimized in a way that mimics the reaction time of human beings, which highly relies on the amount and quality of accumulated evidence from incoming sensory information. What is expected from such a strategy is to produce a short reaction time, whenever the accumulated evidence in favor of a given single choice is strong.

Conversely, reaction time should be longer, whenever evidence is noisy and ambiguous, since more data will be needed to make a reliable decision. Compared to a time-based criterion, this can accommodate the slow intrinsic fluctuations of the electrophysiological signals, which might be due to fluctuations in attention.

In the P300-Speller, this is particularly relevant, since sustained attention is what is required from the subject to keep performing the task efficiently. To implement adaptive decision making, we used a classical entropic measure, which efficiently summarizes and quantifies the uncertainty about our belief, the latter being represented by a probabilistic distribution.

The first significant effect we indeed observed with this new criterion is that, for the same spelling duration, the user is able to spell letters more accurately. The time saved by stopping the flashes earlier, whenever possible, was efficiently reallocated to letters that required longer stimulation time in order to be accurately identified. Equivalently, given an objective in terms of accuracy, fewer flashes should be required with adaptive decision making, on average.

Secondly, a very interesting and significant effect of motivation could be observed online. Indeed, spelling accuracy was found higher for adaptive sessions than for fixed ones when these datasets were reprocessed offline with the same stopping criterion. This suggests that the subjects were on average more engaged into the task during the adaptive session, thus producing electrophysiological responses with a larger signal-to-noise ratio, which resulted in higher spelling accuracies. Indeed, the N1 and P300 responses, which are the electrophysiological responses used to identify the target, are known to reflect the participant's involvement in the task (Treder and Blankertz, 2010). The P300 has also been shown to increase with motivation in a BCI context (Kleih et al., 2010). The fact that spelling accuracy is optimized by continuously and explicitly adapting the stimulation to the user's need appears to create a virtuous cycle by boosting the user's motivation.

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References

Jin J., Allison B.Z., Sellers E.W., Brunner C., Horki P., Wang X. and Neuper C. 2011 An adaptive P300-based control system. *J Neural Eng* **8**, 3:036006.

Kleih S.C., Nijboer F., Halder S. and Kübler A. 2010 Motivation modulates the P300 amplitude during brain-computer interface use. *Clin Neurophysiol* **121**, 7:1023-31.

Rivet B., Souloumiac A., Attina V. and Gibert G. 2009 xDAWN algorithm to enhance evoked potentials: Application to brain-computer interface. *IEEE Trans Biomed Eng* **56**, 8:2035-43.

Serby H., Yom-Tov E. and Inbar G.F. 2005 An improved P300-based brain-computer interface. *IEEE Trans Neural Syst Rehabil Eng* **13**, 1:89-98.

Townsend G., LaPallo B.K., Boulay C.B., Krusienski D.J., Frye G.E., Hauser C.K., Schwartz N.E., Vaughan T.M., Wolpaw J.R. and Sellers E.W. 2010 A novel P300-based brain-computer interface stimulus presentation paradigm: Moving beyond rows and columns. *Clin Neurophysiol* **121**, 7:1109-20.

Treder M.S. and Blankertz B. 2010 (C)overt attention and visual speller design in an ERP-based brain-computer interface. *Behav Brain Funct* **6**, 1:28.

Wolpaw J.R., Birbaumer N., Heetderks W.J., McFarland D.J., Peckham P.H., Schalk G., Donchin E., Quatrano L.A., Robinson C.J. and Vaughan T.M. 2000 Brain-computer interface technology: A review of the first international meeting. *IEEE Trans Rehabil Eng* **8**, 2:164-73.