CoAdapt P300 speller: optimized flashing sequences and online learning

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Abstract

This paper presents a series of recent improvements made on the P300 speller paradigm in the context of the CoAdapt project. The flashing sequence is elicited by a new design called RIPRAND, in which the flashing rate of elements can be controlled independently of grid cardinality. Element-based evidence accumulation allows early-stopping of the flashes as soon as the symbol has been detected with confidence. No calibration session is necessary, thanks to a mixture-of-experts method which makes the initial predictions. When sufficient data can be buffered, subject-specific spatial and temporal filters are learned, with which the interface seamlessly makes its predictions, and the classifiers are adapted online. This paper, which presents results of three online sessions totalling 26 subjects, is the first to report online performance of a P300 speller with no calibration.

1 Material and Methods

The P300 speller presented in this work was implemented in C++ with OpenViBE [7], and a dedicated stimulating software controlled the keyboard display. The software is opensource and part of OpenViBE release 0.18 We used a single Windows laptop to run all software components. The P300 speller keyboard was displayed on a separate LCD screen. A TMSi Refa8 amplifier, synchronized via hardware to the laptop, was used to record from 12 actively shielded electrodes.

The visual stimulations consisted of briefly flashing “smiley” pictures. The P300 wave was detected via 3 channels of an xDAWN spatial filter [8], combined with a Regularized LDA classifier hereforth called RDA, which incorporates a regularisation of the common covariance matrix. The output of the classifier at each flashing time t is denoted $\tilde{y}(t)$.

To save time, elements are always flashed in groups. Initial design of P300 speller groups involved rows and columns of a square matrix [2] or their randomizations [1]. The target element is then found at the intersection of the groups eliciting a P300 response. But repetitively flashing the same groups causes elements within the target groups to be wrongly selected, because of visual attention effects, and because of the contamination of all group elements by classification errors.

Element-wise evidence accumulation avoids these two effects. A different random permutation can then be performed at each repetition of the flashes, effectively changing elements' group membership across repetitions. At each flash t, let the binary vector $\mathbf{a}(t)$ represent the set of n flashed elements within the grid of cardinality N. The score $\boldsymbol{\alpha}(t)$ of each element (initialized to 0 at time 0) is updated with the following scheme, in which both target and non-target flashes contribute to the accumulation:

$$\boldsymbol{\alpha}(t) = \boldsymbol{\alpha}(t-1) + \log\left[\frac{1}{n}\mathbf{a}(t)\tilde{y}(t) + \frac{1}{N-n}(1-\mathbf{a}(t))(1-\tilde{y}(t))\right] \quad (1)$$

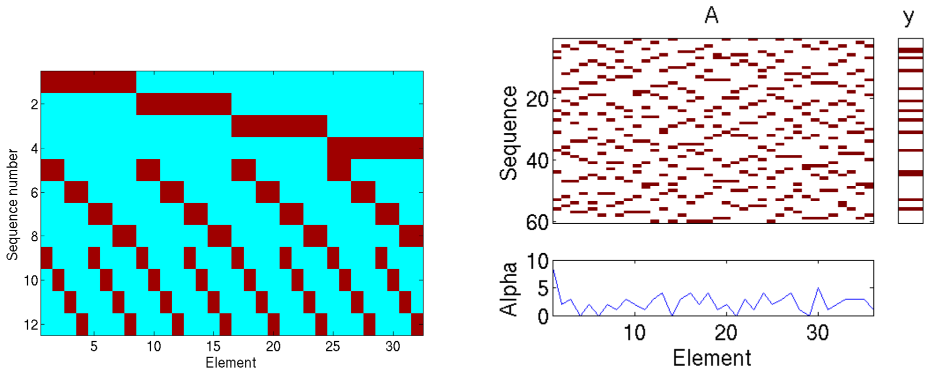


Figure 1: Left: template for a 36-element grid and 1-in-4 flash-rate. Each line represents the flashing elements $\mathbf{a}(t)$. Right: example of accumulation based on the randomized grid on the left, over 60 flashes, with element 1 as target.

The groups' definition, encoded in $\mathbf{a}(t)$, follows a restricted isometry principle (RIP) [10]. This principle offers an minimal intersection between groups, while allowing the **flash-rate to be adapted** (e.g. 1-in-4, 1-in-6, ...), independently of the number of elements. A random permutation of flashed elements is applied after each repetition (RIPRAND). Figure 1 illustrates the RIP (left) and RIPRAND (right) flashing strategies. Large display grids had already been investigated by [11] and [3], but without optimizing the sequences employed for faster search of the target letter.

Another prominent advantage of element-wise accumulation is that it allows ***early stopping*** of flashes, as soon as the score of one element clearly outperforms the others. This Early Stopping has been shown to improve user motivation, and in turn, the quality of the P300 signal [6].

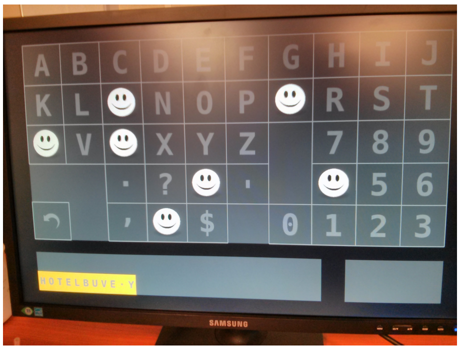
RIPRAND with early stopping was first evaluated offline, using simulated data created by fitting pdfs for P300 detection from a 20-subject database from Inserm Lyon. To test its actual usage, **two online experiments** were performed with 10 subjects each, on a 6x6 grid (**Exp 1**), and on a 9x9 grid (**Exp 2**).

To remove the need for a calibration session, a transfer learning method has been implemented, which uses a **"mixture of experts"** (MOE) classifier learned from the 20-subject data of Experiments 1 and 2. A decision $\tilde{y}(t)$, bounded between 0 and 1, is taken by taking the mean of all binary decisions of the experts. This subject-independent decision is then accumulated using (1).

After the P300 speller has been initialized through the above subject-independent approach, and enough data has been collected, a subject-dependent learning takes place, which exploits the notion of target relabelling: decisions made after the accumulation provide labels for supervised learning. xDAWN and RDA parameters are thus learned, and the RDA parameters are subsequently adapted online, by considering a data buffer.

In summary, the MOE classifier, implemented in OpenViBE, thus replaces the classic calibration phase, after which a new individual classifier is calibrated and the experts are ignored. The individual classifier is updated on the data contained in a buffer (a sliding window, which for the moment has a fixed size).

An **online experiment (Exp 3)** was performed with 6 naive subjects to test the zero-calibration and online learning. Experiment 3 used the keyboard layout displayed on the right. The concepts of zero-calibration and online adaptation have been suggested earlier, and validated offline [5], but this is the first time an online study is presented.



2 Results and discussion

Table 1 (simulated data) shows the advantages of RIPRAND over row-column flashing in reducing the number of flashes required for an accurate selection. Accuracy refers to character selection accuracy (not target detection accuracy). Table 2 presents results from Online Experiments 1 (6x6 grid) and 2 (9x9 grid), with two types of bit-rate: theoretical bit-rate, and actual bit-rate with a 5 second break between characters. In Experiment 1, one subject was disregarded, as he was unable to stay focussed during the session, and his performance degraded, making comparisons delicate. Finally, Table 3 shows results of the session with no calibration: the session starts with a Mixture-of-experts prediction, which quite high accuracy (86.7%) but requires many flashes (88.7 target + non-target per character) to reach a decision. Bit-rate for this initial period is thus quite low (13.8). In the next part of the session, adaptive learning on the users' own data allows the bit-rate to improve to about 30 bits/minute (real bit-rate).

Table 1: Comparison of flashing strategies on simulated data (average over 10000 trials).

Type	Accuracy	Flashes	Theo. Bit-rate
6x6 RIPRAND 1/6	**94.5%**	**34.2**	**62.8**
6x6 Row-Column	93.7%	43.7	47.9
9x9 RIPRAND 1/6	**93.9%**	**42.9**	**63.8**
9x9 Row-Column	87.2%	66.9	37

Table 2: Results of Exp 1 (6x6 grid, averaged over 9 subjects) and Exp 2 (9x9 grid, averaged over 10 subjects). Character selection accuracy, average number of flashes per character selection before early stopping, bit-rate accounting for the 5 s pause between characters, and theoretical bit-rate.

Type	Accuracy	Flashes	Bit-rate	Theo. Bit-rate
6x6 Row-Column	92.2%	21.6	30.1	71.3
6x6 RIPRAND 1/6	**93.3%**	21.6	**31.2**	72.7
9x9 Row-Column	74.5	53.8	18	30.8
9x9 RIPRAND 1/6	**88**	42.1	**26.5**	**47.9**

Table 3: Results of Exp 3 (averaged over 6 subjects). Character selection accuracy, average number of flashes and bit-rate per minute including a 5s pause between characters.

Type	Accuracy	Flashes	Bit-rate
Mixture-of-experts	86.7%	88.7	13.8
Adaptive learning, buffer length 10	**95.7%**	37.7	27.2
Adaptive learning, buffer length 30	94.6%	**27.2**	**30.8**

We have thus developped a new P300 speller paradigm which does not need any calibration session and boosts user motivation thanks to early stopping. A clinical feasibility study is currently taking place at Nice University Hospital on 20 ALS patients. Further improvements considered include the use of Natural Language Models to improve the prediction stage [4, 9] and further improve the bit-rate thanks to word completion.

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