Hybrid oddball - SSVEP BCI

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Abstract

Objectives:
Results:
Conclusion:

1 Introduction

Brain-Computer Interfaces (BCIs) aim at decoding the brain activity in order to provide a direct communication channel between the brain and an external device. In this study, the brain activity is recorded using electroencephalography (EEG), which offer the advantage over other method (*e.g.* micro electrodes, fMRI ...) of being non-invasive and easy to set up.

Some of the earliest EEG-BCI systems were based on the P3 component of the Event Related Potential (ERP) (Donchin et al. 2000; Farwell and Donchin 1988). The P3 is a positive deflection in the EEG time-locked to salient stimuli presented in an oddball paradigm, typically evoked over the parietal cortex, and occurs between 200 and 500 ms after stimulus onset (Sutton et al. 1965). Although those BCIs rely mostly on the P3 component, other components (*e.g.*, occipital N1 and/or N200) may also be used for ERP detection (Bianchi et al. 2010; Kaufmann et al. 2011), for this reason we prefer here to use the term *oddball-based BCIs*. Such system have been shown to work successfully on both healthy and disabled subjects (Combaz et al. 2013; Krusienski et al. 2008; Sellers et al. 2010). However, as they rely on several repetition of a stimuli sequence in order to increase the signal-to-noise ratio of the ERP, they remain slow and the communication speed decreases as the number of stimuli (*i.e.* number of choices available to the user) increases.

Other systems of interest are BCIs based on Steady-State Visually Evoked Potentials (SSVEPs). They rely on the psychophysiological properties of the EEG brain responses recorded from the occipital cortex during the periodic presentation of identical visual stimuli (*i.e.* flickering stimuli). When the periodic presentation is at a sufficiently high rate (> 6 Hz), stable and synchronized neural oscillations at the stimulus frequency and its harmonics are evoked over the visual cortex (Herrmann 2001; Luck 2005; Regan 1966). Several SSVEP-based BCIs have been successfully tested with healthy subjects (see Vialatte et al. 2010 for a review) and only recently (to a lesser extend) with locked-in patients (Combaz et al. 2013; Parini et al. 2009). Such BCIs have the advantage of a relatively fast detection, however, particularly when working with on-screen stimulation, the number of usable stimulation frequencies is limited (Bin et al. 2009).

Recently, the BCI community started to develop *hybrid BCIs*, which combine different data acquisition modalities in order to improve the user experience of the system. As defined by Pfurtscheller et al. (2010), *"a typical hybrid BCI is composed of one BCI and another system (which might be another BCI), and must also achieve specific goals better than a conventional system"*. We focus here on the case where both system are BCIs. The improvement achieved by a hybrid system can be of different natures such as higher accuracy, larger number of choice, higher selection speed, access to a no-control state, better usability or higher number of person effectively able to use the system (Brunner et al. 2011).

A hybrid BCI can be designed in a way that both modalities encode the same command, so that each of them could theoretically be used independently to make a decision. Such system could help decreasing BCI illiteracy (subject could compensate a weak control with one modality with a better control of the other) and/or increase the detection accuracy. For example, Allison, Brunner, Kaiser, et al. (2010) showed in an offline analysis that Event Related Desynchronization (ERD) and SSVEP activity could be simultaneously elicited and detected and could lead to a wider number of people being able to control a two-choice BCI. They however observed in a later study analysing online data (Brunner et al. 2011), that there was no significant difference between the pure SSVEP and the hybrid condition. An other example is the study from Xu et al. (2013) where the authors combine detection of oddball response and detection of the interruption of SSVEP response in a nine targets BCI to improve the accuracy of the BCI.

Other hybrid systems can be designed in a way that one modality can operate on its own while the other modality provides additional information helping to make the decision without being able to operate on its own. This is the case of the study published by Yin et al. (2013) where the authors use SSVEP activity to increase the performance of an oddball-based spelling BCI.

A last example of hybrid design is where each modality provides the system with independent commands that are then combined to result in a more complex control. For example, Allison, Brunner, Altstätter, et al. (2012) developed a BCI where the user could control a cursor on a two dimensional screen where ERD activity encoded vertical movement of the cursor and SSVEP activity encoded horizontal movement.

To our knowledge, no design of such *independent hybrid BCI* combining the detection of SSVEP activity and oddball ERP has been reported on in the literature. Neither has been proposed a study reporting on the influence of SSVEP stimulation on the oddball response and the influence of visual oddball stimulation on SSVEP responses with respect to the frequency used for the SSVEP stimulation.

We investigate the possibility to combine those two modalities in a way that would results in a system being able to operate faster than a purely oddball-based BCI and encoding more targets than a purely SSVEP-based BCI would. We aim here at studying the interactions between the two types of brain responses and the possibility of such a hybrid BCI in a series of experiments where EEG data are analysed offline. This is a necessary first step before studying the differences in online performances between a hybrid system and purely oddball and SSVEP based ones.

We report in this study on three series of experiment aiming at 1) studying the effect of a SSVEP stimulation at different frequencies on the oddball response and its detection accuracy, 2) studying the effect of oddball stimulation on the SSVEP response for different frequencies, 3) assessing the possibility to detect simultaneously both type of brain activity in a proof-of-concept experiment.

2 Materials and Methods

2.1 Material

The EEG signals were recorded using a BioSemi Active Two system with 32 channels (following the 10-20 international system) at a sampling rate of 1024 Hz. Two additional electrodes were positioned on the right and left mastoids and the mean of the signals recorded at those two sites was used to reference the activity measured by the 32 EEG electrodes.

All stimulation employed MATLAB®, the stimuli were visually presented on a laptop's LCD screen (60 Hz refresh rate) and their display and timing used the *Psychophysics Toolbox Extensions* (Brainard 1997; Pelli 1997).

The EEG data were processed using MATLAB® and all statistical analyses were performed using R (R Core Team 2013) and mixed effect models (Pinheiro and D. M. Bates 2000) were fitted with the R package *lme4* (D. Bates et al. 2013).

2.2 Experimental protocol

2.2.1 Experiment 1: studying the oddball ERPs

The aim of this first experiment was to study the effect of a flickering background on the typical ERP response associated to an oddball paradigm. Nine subjects participated in the experiment (age, gender).

As shown in Fig. 1, a typical *stimulation cycle* (or *trial*), started with a 2000 ms cue, indicating the participant his/her target item, followed by a 1000 ms pause during which the cue disappeared and all icons remained gray. The background rectangle started then to flicker and the oddball stimulation began 500 ms later. The oddball stimulation consisted of 10 *flashing sequences* during which each of the 6 icons was flashed one after another in random order for a duration randomly set between 200 and 300 ms. As usually done for oddball experiments, the participants were instructed to focus on their target symbol and count the number of time it flashes. A 1000 ms pause followed the oddball stimulation and preceded the next cue. An *experimental run* lasted approximately 4 minutes and consisted of 12 consecutive trials, so that each of the 6 icons was cued twice (in random order).

As we aimed here at studying the effect of the flickering background on the oddball ERP response, we considered 5 experimental conditions. The first one (*baseline condition*) consisted of a run as described in the previous paragraph but in which no flickering background was displayed. The 4 other conditions (*hybrid conditions*) differed only by the frequency of the flickering background; the frequencies used were 8.57, 10, 12 and 15 Hz, corresponding to the division of the refreshing rate of the screen by 7, 6, 5 and 4, respectively.

For each of the 5 conditions, all subjects performed 3 runs, therefore the whole experiment consisted of 15 runs of approximately 4 minutes each (12 trials per run). The order of the run was randomized for each subject and a 5 to 10 minutes pause was set up every 5 runs.

2.2.2 Experiment 2: studying the SSVEP responses

The aim of this second experiment was to study the effect of an oddball paradigm on the SSVEP responses. N subjects participated in the experiment (age, gender).

The experimental run was the same as described in sec. 2.2.1. Two experimental parameters were manipulated, the first one was the stimulation frequency; the same frequencies as for the first experiment were used (8.57, 10, 12 and 15 Hz). The second experimental parameter was the presence or not of the oddball stimulation sequence. When the oddball stimulation was displayed, the participants were instructed to count the number of flashes of the target icon, while when no oddball stimulation was displayed, their task was simply to focus on their target icon.

The experiment consisted thus of 8 runs of approximately 4 minutes each (12 trials per run). The order of the run was randomized for each subject and a 5 to 10 minutes pause was set up after the first 4 runs.

2.2.3 Experiment 3: hybrid classification

This third experiment consists in a proof-of-concept for a hybrid oddball-SSVEP BCI. N subjects took part in the experiment.

Two rectangles flickering at 12 Hz and 15 Hz where simultaneously presented on the left and right side of the screen, respectively. Within each of those rectangles 6 items were presented so that 2 independent and simultaneous oddball paradigm could occur as shown in Fig. 2. The *stimulation cycle* was the same as described in sec. 2.2.1, icons from the left and right rectangles were always flashed simultaneously, however the order in which the icons would be flashed was set independently (and randomly) for each rectangle. An *experimental run* lasted approximately 4 minutes and consisted of 12 consecutive trials (with 10 repetitions of the flashing sequence for each), so that each of the 12 icons was cued once (in random order). Each subject participated in 8 consecutive runs with a 5 to 10 minutes pause after the the 4$^{\text{th}}$ run.

2.3 Data Analysis

2.3.1 Experiment 1: Observing the ERPs

We first observed average responses to target stimuli for each of the 5 experimental conditions. The EEG signals were filtered between 0.3 and 30 Hz (zero-phase 3$^{\text{rd}}$ order Butterworth filter) and epochs were cut from 200 ms before the stimuli onsets until 800 ms after. In order to ensure that none of the epochs used for averaging were corrupted by ocular artifact, we rejected, for each *experimental run*, the 15% epochs with the highest peak-to-peak amplitude (Luck 2005). We also visually inspected the filtered EEG traces to verify that no of ocular artifact could be seen within the 85% remaining epochs. For each participant, averaged ERPs were observed and compared with respect to the experimental condition. We particularly looked for differences between the baseline condition (pure oddball) and the hybrid conditions (4 other condition with flickering square)

To assess differences and similarities, we calculated for each subject and EEG channel the correlation coefficient between average ERPs for all *conditions pairs* (5 experimental condition, 10 condition pairs, *e.g.* oddball/hybrid-10Hz, hybrid-12Hz/hybrid-10Hz, *etc*). Those correlation data were modelled with a linear-mixed effect model with the channels nested within subjects as a random effect and the condition pair as a fixed effect. Post-hoc pairwise comparisons for each level of the *conditions pair* factor were conducted via Tukey's test (using the *multcomp* R package, Hothorn et al. 2008). The significance level was $\alpha = 0.01$.

2.3.2 Experiment 1: Classifying the ERPs

The second step was to compare classification accuracies. The EEG signals were filtered between 0.5 and 20 Hz (zero-phase 3$^{\text{rd}}$ order Butterworth filter), epochs were cut from each the stimuli onsets until 600 ms after and downsampled to 128 Hz. The resulting epochs were labeled to either *target epochs* or *non-target epochs* according to whether they corresponded to the EEG response to a target stimulus (flashing of a target symbol) or a non-target one (flashing of any non-target symbol). For each subject and experimental condition, we ran a 3-fold cross-validation where a linear Support Vector Machine (SVM) was trained (Keerthi and DeCoste 2006) on the data collected during 2 out of the 3 experimental runs and the performance was measured on every trials of the remaining run.

For each trial, the SVM returns a score associated with each of the 6 icons and the icon with the highest score is identified as *detected target*. We then derive a *correctness value* set to 1 if the detected target matches the cued icon (correct detection) and 0 otherwise. We thus obtain for each subject and experimental condition 36 correctness values. The correctness values were computed for a number of repetitions N_r of the flashing sequence varying from 1 to 10. In order to mimic the behavior of a BCI, for each trial and each icon, epochs were average over the N_r *first repetitions*.

The correctness data were modelled using a logistic mixed effect models (Jaeger 2008) with the number of repetitions nested within subjects as random factors. As fixed effects, we considered the experimental condition (5 levels factor), the number of repetitions (10 levels factor) and the interaction between those 2 factors. In order to assess of the influence of the experimental condition on the classification correctness we compared this model to a reduced version of it where the experimental condition factor (and all interactions involving this factor) was removed from the fixed effects. Both models were fitted using the *maximum likelihood* method and the p-value was obtained by a *likelihood ratio test* of the 2 models (Pinheiro and D. M. Bates 2000).

2.3.3 Experiment 1: single *v.s.* multiple oddball classifier(s)

In the previous section, we measure performances by building one classifier for each subject and condition. More specifically, for each hybrid condition (8.57, 10, 12 and 15 Hz), a specific oddball ERP classifier is trained. In a hybrid oddball-SSVEP BCI, where several visual oddball paradigms occur simultaneously within SSVEP stimuli flickering at different frequencies, it does not seem convenient to have as many ERP classifiers as stimulation frequencies. First it would compromise the usability of the BCI by increasing the time needed for training, and second, as the target frequency is not known (this is the role of the SSVEP classifier to find it out), one would have to either rely on the SSVEP classifier to decide which ERP classifier to apply or to find an optimal design that combines the different ERP (and eventually SSVEP) classifiers in order to identify the target ERP.

Ideally, it would be more appropriate to have a single ERP classifier trained on data recorded in all conditions. However this should not be done at the expense of a loss in detection accuracy. We thus compared accuracies of oddball ERP detection for data recorded in the hybrid condition obtained from classifiers built individually for each condition (as described in the previous section) to the accuracies resulting from a single classifier trained on all data recorded in the different hybrid conditions.

As in the previous section, we modelled the correctness data using a logistic mixed effect models (Jaeger 2008) with the number of repetitions nested within subjects as random factors. As fixed effects, we considered the experimental condition (4 levels factor), the number of repetitions (10 levels factor), the type of classifier (2 levels factor) and all interactions between those 3 factors. In order to assess of the influence of the classifier on the classification correctness we compared this model to a reduced version of it where the classifier factor (and all interactions involving this factor) was removed from the fixed effects. Both models were fitted using the *maximum likelihood* method and the p-value was obtained by a *likelihood ratio test* of the 2 models (Pinheiro and D. M. Bates 2000).

2.3.4 Experiment 2: SSVEP response analysis

For each trial we estimated the power of the EEG signal measured by the Oz channel in the frequency corresponding to the stimulation frequency of the trial. The power was estimated every second from 1 to 14 seconds of stimulation in the following way (Friman et al. 2007):

$$P(Y, f) = \left[\sum_{i=1}^{n_s} y_i \times \cos(2\pi i f / f_s)\right]^2 + \left[\sum_{i=1}^{n_s} y_i \times \sin(2\pi i f / f_s)\right]^2 \tag{1}$$

where f is the frequency of interest in Hz, f_s is the sampling frequency of the EEG signal (1024 Hz in our case) and $Y = [y_1, y_2, ..., y_{n_s}]$ is the vector representing the n_s first samples of EEG data after the SSVEP stimulation onset ($n_s = f_s$ for a 1 s signal, $n_s = 2f_s$ for a 2 s signal, *etc*), .

We obtain thus for each subject, run and trial, one *growth curves* corresponding to the evolution of the power of the signal in the stimulation frequency along stimulation time.

We modelled these power data using a linear mixed effect regression model (Pinheiro and D. M. Bates 2000). We considered as fixed factor the stimulation duration (continuous variable, quadratic model), the stimulation frequency (4 levels factor), the presence of the oddball stimulation (2 levels factor) and all interactions betweens those 3 factors. We allowed the model intercept and slopes (*w.r.t.* the stimulation duration) to vary randomly for each subject and for each trial within subject.

In order to assess of the influence of the oddball stimulation on the power response we compared this model to a reduced version of it where the oddball stimulation factor (and all interactions involving this factor) was removed from the fixed effects. Both models were fitted using the *maximum likelihood* method and the p-value was obtained by a *likelihood ratio test* of the 2 models (Pinheiro and D. M. Bates 2000).

2.3.5 Experiment 3: hybrid classification

For the oddball ERP classification, we used the 2 first runs for training the classifiers and the 6 remaining runs to measure the detection accuracy. We used the same procedure as described in sec. 2.3.1 to build a linear SVM classifier on the training data and measure the performance on the test data with respect to the number of repetitions of flashing sequence. We thus obtain, for each number of repetitions, 72 binary values representing the correctness of detection for each of the 12 trials that compose all 6 testing runs.

For the SSVEP detection, the EEG signals were first filtered between 0.2 and 40 Hz (zero-phase 4^{th} order Butterworth filter), and downsampled to 256 Hz. For the detection itself we used a technique proposed by Friman et al. (2007) (also applied by Chumerin et al. 2011; Segers et al. 2011). This technique consists in first applying a spatial filter to the EEG data following the *Minimum Energy Combination* method suggested by Friman et al. (2007). It results in a set of linear combinations of the original EEG signals for which the noise is minimized at the frequencies of interest (*i.e.* the 4 stimulation frequencies) and their harmonics. In the second step, a scoring function was calculated for each of the 2 stimulation frequencies and the one with the highest score was identified as the target frequency. The scoring function corresponds to the average of the signal-to-noise ratio across harmonics and components of the spatially filtered signals. The signal-to-noise ratio was calculated as the ratio of the estimated signal power and the estimated noise power at the desired frequency (see Chumerin et al. 2011; Friman et al. 2007 for details).

The icon detection correctness was determined by combining oddball ERP detection correctness and SSVEP detection correctness. Both the ERP and the SSVEP frequency needed to be correctly detected for the icon to be correctly identified. The correctness values for ERP, SSVEP and icon detection were measured for the N_r first repetitions of the flashing sequence, with N_r varying from 1 to 10.

Besides icon detection accuracy, we also measured the Information Transfer Rate (ITR, see for example McFarland et al. 2003; Nijboer et al. 2010; Serby et al. 2005; Wolpaw et al. 2000) expressed in *bits per minute* and defined as:

$$I = B \times \frac{N_c}{\sum_{i=1}^{N_c} t_i} \times 60 \tag{2}$$

where N_c is the number of symbols communicated, t_i the time in seconds needed to communicate the i^{th} symbol and B the bitrate expressed in bits per symbols and defined by:

$$B = \log_2(N) + p\log_2(p) + (1-p)\log_2(\frac{1-p}{N-1}) \tag{3}$$

where p is the classification accuracy and N the number of possible symbols to communicate.

3 Results

3.1 Experiment 1: observing the oddball ERPs

The average responses to target stimuli of each of the 5 experimental conditions for all subjects and a selection of EEG channels covering the scalp from frontal to occipital locations are shown in Fig. 3 and Fig. 4. One can notice that for most subjects and some EEG channels, the ERP corresponding the 4 hybrid conditions are very similar while the ERP corresponding to the oddball condition stands out.

This difference between oddball and hybrid ERPs can be of a different nature depending on the subject and the channel observed. It takes the form of a time shift as observed for subjects S03 and S05 in the frontal and central channels, where the positive peak observed between 200 ms and 300 ms appears slightly earlier for the oddball condition than for the hybrid conditions. It can also take the form of a difference in peak amplitude as one can see in the ERPs from subject S02 where the negative peak observed in the parietal electrodes between 100 ms and 200 ms is characterized by a stronger magnitude in the oddball condition than in the hybrid conditions. Similarly, the ERPs from subject S06 in the central and parietal channels are characterized by one negative peak at around 150 ms and a positive one at around 200 ms, both peaks showing stronger magnitude in the oddball condition than in the hybrid ones.

One can also observe differences in both amplitude and latencies as for the ERPs recorded for subject S02 by the occipital channels where the positive peak between 200 ms and 300 ms appears earlier with a stronger magnitude in the oddball condition than in the hybrid ones. Similarly the ERPs recorded for subject S09 in the frontal and central channels between 100 ms and 200 ms appear earlier and have a stronger magnitude for the oddball condition than for the hybrid ones.

Although the nature of the differences is not systematic across subjects in terms of scalp location, polarity, latency and amplitude, the fact that there are differences between ERPs corresponding to the oddball condition on one side and the hybrid conditions on the other side seems quite systematic. In Fig. 5, we show for each subject and channel the correlation values between the mean ERP corresponding to each pair of condition. We distinguish correlation values between 2 hybrid ERPs (red dots on Fig. 5) from correlation values between the oddball ERP and an hybrid ERP (blue dots on Fig. 5). The figure seems to suggest that the correlation value is typically lower when it is measure between the oddball ERP and an hybrid ERP.

In Table 1, we show the results for the post-hoc pairwise comparisons (Tukey's test) for the model build on those correlation data (see sec. 2.3.3 for description). It appears that, on the one hand, the correlation between the oddball and every hybrid ERP was always significantly lower than the correlation between any 2 hybrid ERPs, while, on the other hand, no significant difference was observed between correlation values measure for 2 different pairs of hybrid ERPs.

3.2 Experiment 1: classifying the oddball ERPs

The results from the previous section support the observations made from Fig. 3 and Fig. 4 that although the differences between ERPs recorded in different hybrid condition do not seem to differ much, there appear to be clear differences between the oddball ERPs and the hybrid ones. However, from a BCI oriented point of view, the question is not so much about the differences in the shape of the ERPs but more about differences in classification accuracy. We aim here at assessing whether the classification accuracy (using the method described in sec. 2.3.2) varies significantly from one condition to another.

The average detection correctness with respect to the number of repetitions considered is shown in Fig. 6 for each subject and for the subject grand-average. As this is typically the case for oddball-based BCIs, we observe an increase in detection accuracy with respect to the number of repetitions. The figure does not suggest any clear and systematic difference in accuracy between the 5 experimental conditions. This observation was supported by our statistical analysis (see description in sec. 2.3.2), no significant effect of the experiment condition on the detection correctness was observed ($\chi^2(40) = 40.08$, $p = 0.467$).

3.3 Experiment 1: single *v.s.* multiple oddball classifier(s)

In Fig. 7 we show the detection accuracies (subject mean) with respect to the number of repetitions considered for each of the 2 classifiers described in sec. 2.3.3. The red curves represent results from building one specific classifier for each hybrid condition, the blue curves represent results from building one general classifier and applying it to the test data from all hybrid conditions. For all 4 conditions we can observe typically higher accuracies for the general classifier than for the specific ones.

The comparison of the statistical models described in sec. 2.3.3 confirmed that the difference between the accuracies resulting from 2 classifying approaches was statistically significant ($\chi^2(40) = 138.46$, $p = 8.908e-13$).

3.4 Experiment 2: studying the SSVEP responses

Average power values with respect to the stimulation time are shown in Fig. 8 for each subject, stimulation frequency and oddball condition. The figure does not suggest any obvious difference between the baseline (pure SSVEP) and the hybrid (SSVEP combined with oddball stimulation) conditions. It however shows a great variability of the evolution of the power along time across subject, as shown by the difference in magnitude on the ordinate scales of the figure. The error bars suggest also an important trial-to-trial variability within each subject and condition. This variability is illustrated in Fig. 9 where we show the profile response along time of each single trial for subjects S2 and S5 corresponding to the 15 Hz stimulation frequency for both baseline and hybrid condition.

The comparison of the mixed models described in sec. 2.3.4 did not show any significant effect of the oddball stimulation on the power of the brain response to the SSVEP stimulation ($\chi^2(12) = 14.05$, $p = 0.298$).

3.5 Experiment 3: hybrid classification

In Fig. 10 and Fig. 11, we show the accuracy and ITR values, for oddball ERP, SSVEP and symbol detection with respect to the number of repetitions considered for all subjects and averaged over subjects. As for a symbol to be correctly detected, both oddball ERP and SSVEP frequency need to be identified, the symbol accuracy is bounded by both oddball ERP and SSVEP detection accuracies. Results show that 2 repetitions of the flashing sequence (3 s of stimulation) was enough for all subjects except S06 to reach a symbol detection above 70%, which is commonly accepted as a minimum criterion level necessary for communication (Brunner et al. 2011; Combaz et al. 2013; Kübler and Birbaumer 2008; Kübler, Neumann, et al. 2004).

Although the symbol detection accuracy is necessarily lower the ones of oddball ERP and SSVEP detection, it offers a larger choice of items to communicate than those two modalities (12 *versus* 6 for the oddball ERP detection and 2 for the SSVEP detection). As shown in Fig. 11, the ITR values were typically higher for the symbol detection than for the oddball ERP and SSVEP detection.

4 Discussion

4.1 Optimal training of the oddball ERP classifier

In our first experiment, we show that adding a flickering stimulus in the background of a visual oddball stimulation does not affect the detection accuracy of the oddball ERP. This result is obviously only valid in the framework of the signal processing and classification methods used in the study. It nevertheless shows that despite the disturbance due the SSVEP distracting stimulation, it is possible to detect the oddball ERP without loosing accuracy. An other important result is that we did not observe any significant difference in accuracy for the hybrid condition with respect to the stimulation frequency used for the SSVEP stimulation. Those results indicate that having a SSVEP stimuli flickering in the background of a visual oddball paradigm should not deteriorate the oddball ERP detection, no matter the frequency used (at least for the 4 frequencies tested in this study).

We also observed that, for a given dataset of ERPs recorded in a hybrid oddball-SSVEP condition with different SSVEP stimulation frequencies, using a single general classifier for the oddball ERP detection leads to higher accuracies than using multiple specific classifiers for each SSVEP stimulation frequency. An important difference between the 2 approaches is that, since both classifiers use all the training data available, the single classifier uses a training dataset that is 4 times larger than that of each of the specific classifiers. This could explain the difference obtained between the 2 approaches. To verify this, we measured accuracies of oddball ERP detection obtained when using a single classifier that was trained on one fourth of the training data (uniform representation of all 4 conditions and random selection within each condition) so that the amount of training data used to build this classifier would be the same as for each of the specific classifiers. We show the resulting accuracy along with the ones obtained with the specific classifiers in Fig. 12. The difference is much less noticeable than when using all the training data for the single classifier (see Fig. 7). The statistical analysis confirmed that the difference between the accuracies resulting from 2 classifying approaches was not significant ($\chi^2(40) = 28.31$, $p = 0.917$).

This means that the better performance obtained with the single classifier using all training data with respect to the performance obtained by multiple specific classifiers is solely due to the difference in size of the training datasets. This does not come as surprise considering the similarities of the oddball ERPs recorded in the different hybrid conditions as depicted in Fig. 3 and Fig. 4.

Indeed since those ERPs did not seem to show systematic differences, building separate classifiers for each condition would be similar to having one single dataset of ERPs, splitting it randomly in separate group and training one classifier per group. While, on the other hand, simply training one classifier on the whole dataset would make an more optimal use of the available data.

4.2

The second experiment showed that adding a visual oddball paradigm on top of a SSVEP stimulation did not affect significantly the power of the EEG response to the SSVEP stimulation in the concerned frequency. The SSVEP classification procedure described in sec. 2.3.5 relies on computing scores associated to different competing stimuli in order to attempt to identify the target stimulus. As our second experiment did not consider multiple competing stimuli (for each run, only one SSVEP stimulus at a specific frequency was shown on the screen), we did not attempt to classify the SSVEP responses.

4.3

The results from our 2 first experiments suggest the possibility of building a hybrid visual oddball-SSVEP BCI where both stimulations would physically overlap without compromising the detection of any of the 2 types of evoked response. Our third experiment confirmed those results showing the possibility of detecting both oddball ERPs and SSVEP activity simultaneously, and the results obtained suggest not only the feasibility of such hybrid BCI system but also a possible advantage of those systems over pure oddball and SSVEP ones in terms of communication rate.

5 Conclusion

Acknowledgments

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Table 1: Results from the post hoc pairwise comparisons of the linear mixed model built on the correlation data shown in Fig. 5. The first column represents the tested hypothesis; "odd" represents the oddball condition while "h08", "h10", "h12" and "h15" represent the hybrid condition at 8.57, 10, 12 and 15 Hz, respectively. Therefore "corr(odd,h10)" represents the correlation between oddball and 10 Hz-hybrid ERPs. The first line of the table tests for significance in the difference between, on the one hand, correlation values between ERPs recorded in the oddball and in the 10 Hz-hybrid conditions and, on the other hand, correlation values between ERPs recorded in the oddball and in the 8.57 Hz-hybrid conditions. The second column shows the estimate of the tested difference (reported in the first column), the third and fourth columns represent respectively the test statistic and the associated p-value. the symbol ** denotes statistical significance below 0.01.

Null hypothesis	Estimate	z-value	p-value	
corr(odd,h10) - corr(odd,h08) == 0	−0.019706	−3.152	0.05165	
corr(odd,h12) - corr(odd,h08) == 0	0.004923	0.787	0.99877	
corr(odd,h15) - corr(odd,h08) == 0	0.020458	3.272	0.03563	
corr(h08,h10) - corr(odd,h08) == 0	0.105049	16.800	< 0.001	**
corr(h08,h12) - corr(odd,h08) == 0	0.110026	17.596	< 0.001	**
corr(h08,h15) - corr(odd,h08) == 0	0.095337	15.247	< 0.001	**
corr(h10,h12) - corr(odd,h08) == 0	0.108974	17.428	< 0.001	**
corr(h10,h15) - corr(odd,h08) == 0	0.093076	14.885	< 0.001	**
corr(h12,h15) - corr(odd,h08) == 0	0.108701	17.384	< 0.001	**
corr(odd,h12) - corr(odd,h10) == 0	0.024629	3.939	0.00331	**
corr(odd,h15) - corr(odd,h10) == 0	0.040164	6.423	< 0.001	**
corr(h08,h10) - corr(odd,h10) == 0	0.124755	19.952	< 0.001	**
corr(h08,h12) - corr(odd,h10) == 0	0.129732	20.748	< 0.001	**
corr(h08,h15) - corr(odd,h10) == 0	0.115043	18.399	< 0.001	**
corr(h10,h12) - corr(odd,h10) == 0	0.128680	20.580	< 0.001	**
corr(h10,h15) - corr(odd,h10) == 0	0.112782	18.037	< 0.001	**
corr(h12,h15) - corr(odd,h10) == 0	0.128407	20.536	< 0.001	**
corr(odd,h15) - corr(odd,h12) == 0	0.015536	2.485	0.27621	
corr(h08,h10) - corr(odd,h12) == 0	0.100126	16.013	< 0.001	**
corr(h08,h12) - corr(odd,h12) == 0	0.105104	16.809	< 0.001	**
corr(h08,h15) - corr(odd,h12) == 0	0.090415	14.460	< 0.001	**
corr(h10,h12) - corr(odd,h12) == 0	0.104052	16.641	< 0.001	**
corr(h10,h15) - corr(odd,h12) == 0	0.088153	14.098	< 0.001	**
corr(h12,h15) - corr(odd,h12) == 0	0.103779	16.597	< 0.001	**
corr(h08,h10) - corr(odd,h15) == 0	0.084591	13.528	< 0.001	**
corr(h08,h12) - corr(odd,h15) == 0	0.089568	14.324	< 0.001	**
corr(h08,h15) - corr(odd,h15) == 0	0.074879	11.975	< 0.001	**
corr(h10,h12) - corr(odd,h15) == 0	0.088516	14.156	< 0.001	**
corr(h10,h15) - corr(odd,h15) == 0	0.072618	11.614	< 0.001	**
corr(h12,h15) - corr(odd,h15) == 0	0.088243	14.112	< 0.001	**
corr(h08,h12) - corr(h08,h10) == 0	0.004977	0.796	0.99866	
corr(h08,h15) - corr(h08,h10) == 0	−0.009712	−1.553	0.87030	
corr(h10,h12) - corr(h08,h10) == 0	0.003925	0.628	0.99980	
corr(h10,h15) - corr(h08,h10) == 0	−0.011973	−1.915	0.65867	
corr(h12,h15) - corr(h08,h10) == 0	0.003652	0.584	0.99989	
corr(h08,h15) - corr(h08,h12) == 0	−0.014689	−2.349	0.35713	
corr(h10,h12) - corr(h08,h12) == 0	−0.001052	−0.168	1.00000	
corr(h10,h15) - corr(h08,h12) == 0	−0.016950	−2.711	0.16927	
corr(h12,h15) - corr(h08,h12) == 0	−0.001325	−0.212	1.00000	
corr(h10,h12) - corr(h08,h15) == 0	0.013637	2.181	0.47005	
corr(h10,h15) - corr(h08,h15) == 0	−0.002261	−0.362	1.00000	
corr(h12,h15) - corr(h08,h15) == 0	0.013364	2.137	0.50087	
corr(h10,h15) - corr(h10,h12) == 0	−0.015898	−2.543	0.24536	
corr(h12,h15) - corr(h10,h12) == 0	−0.000273	−0.044	1.00000	
corr(h12,h15) - corr(h10,h15) == 0	0.015625	2.499	0.26860	

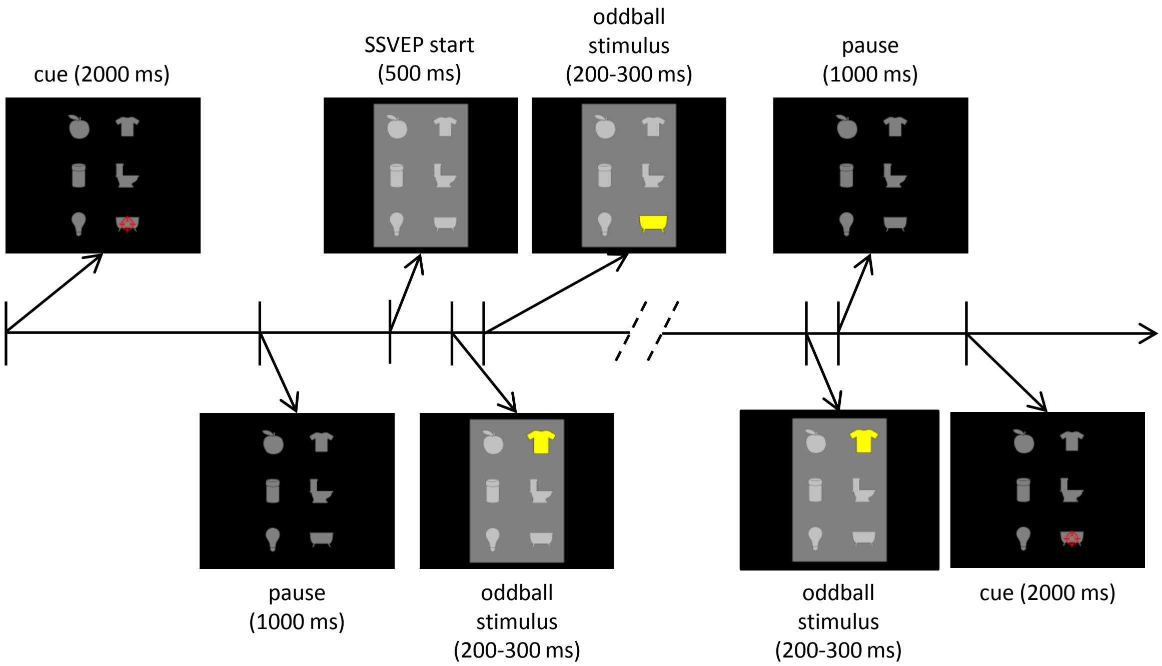

Figure 1: stimulation sequence

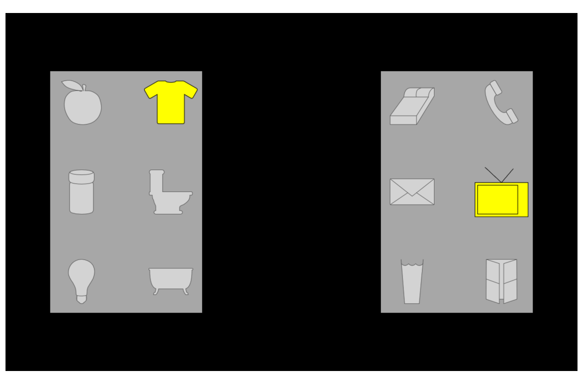

Figure 2: example of stimulus

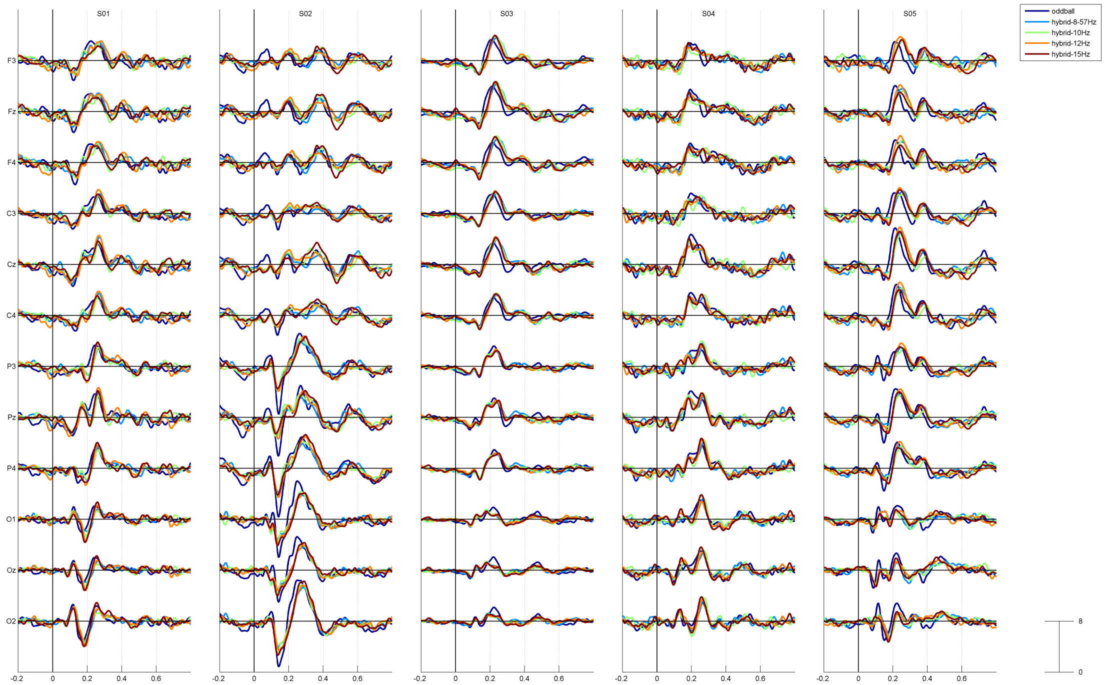

Figure 3: Average ERP responses to the target stimuli for a selection of EEG channels covering the scalp from frontal to occipital locations for all 5 experimental conditions for subjects S01 to S05. Time 0 represents the stimuli onset

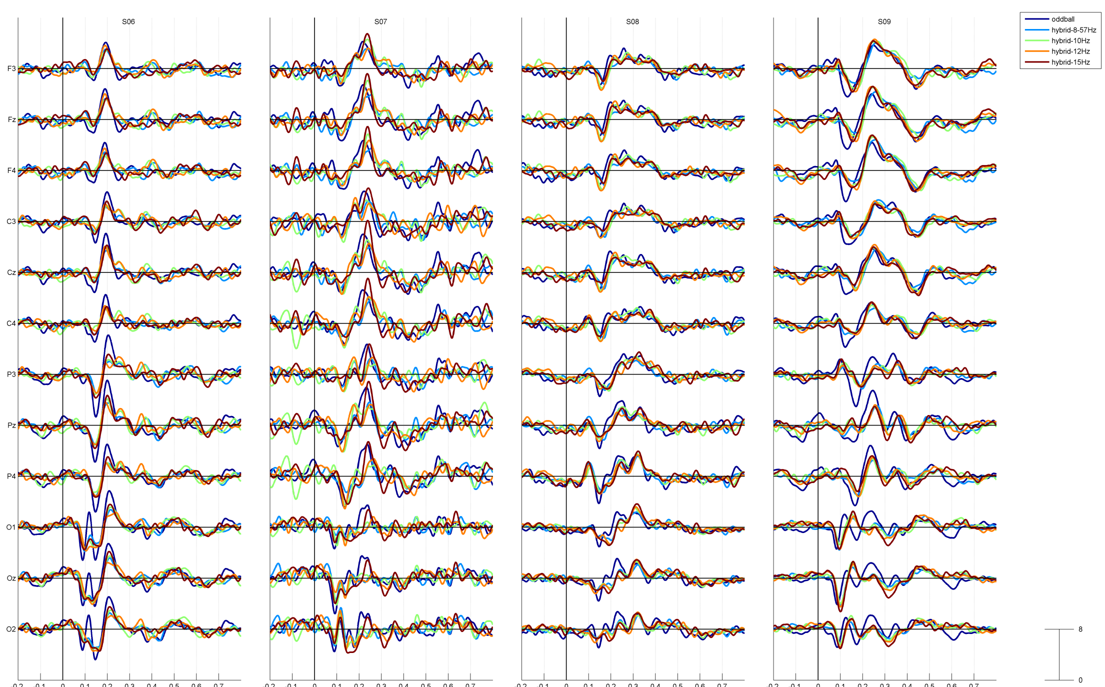

Figure 4: Average ERPs responses to the target stimuli for a selection of EEG channels covering the scalp from frontal to occipital locations for all 5 experimental conditions for subjects S06 to S09. Time 0 represents the stimuli onset

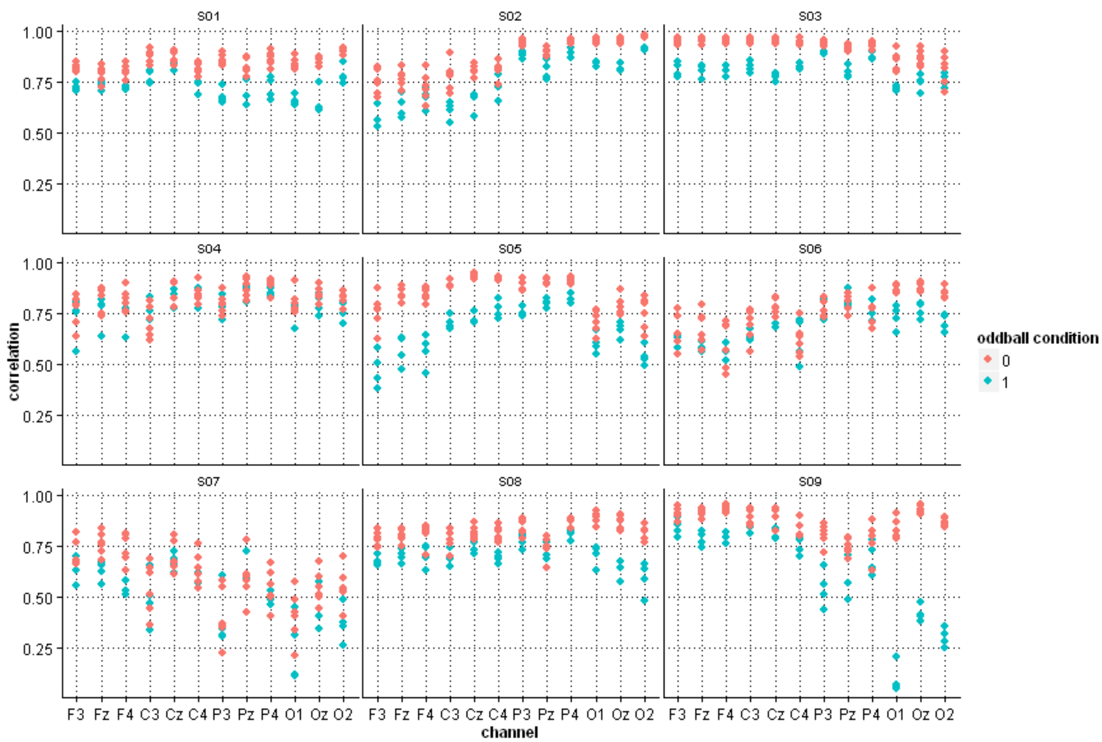

Figure 5: Pairwise correlations between ERPs for all condition per subject and EEG channel. The blue dots represent correlation values measures between the average ERP recorded in the oddball condition and the average ERP recorded in each of the 4 hybrid conditions while the red dots represent correlation values measured between 2 average ERPs recorded in different hybrid condition.

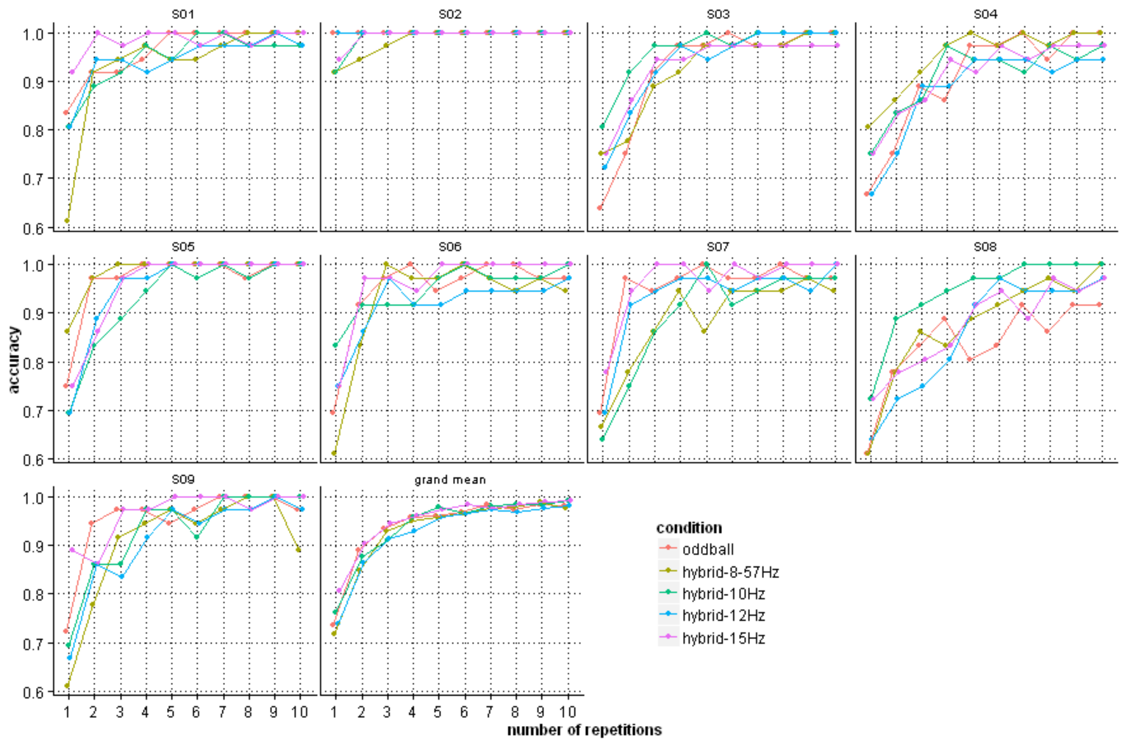

Figure 6: Accuracy of oddball ERP detection with respect to the number of repetitions considered for each experimental condition, for each subject and averaged over subjects.

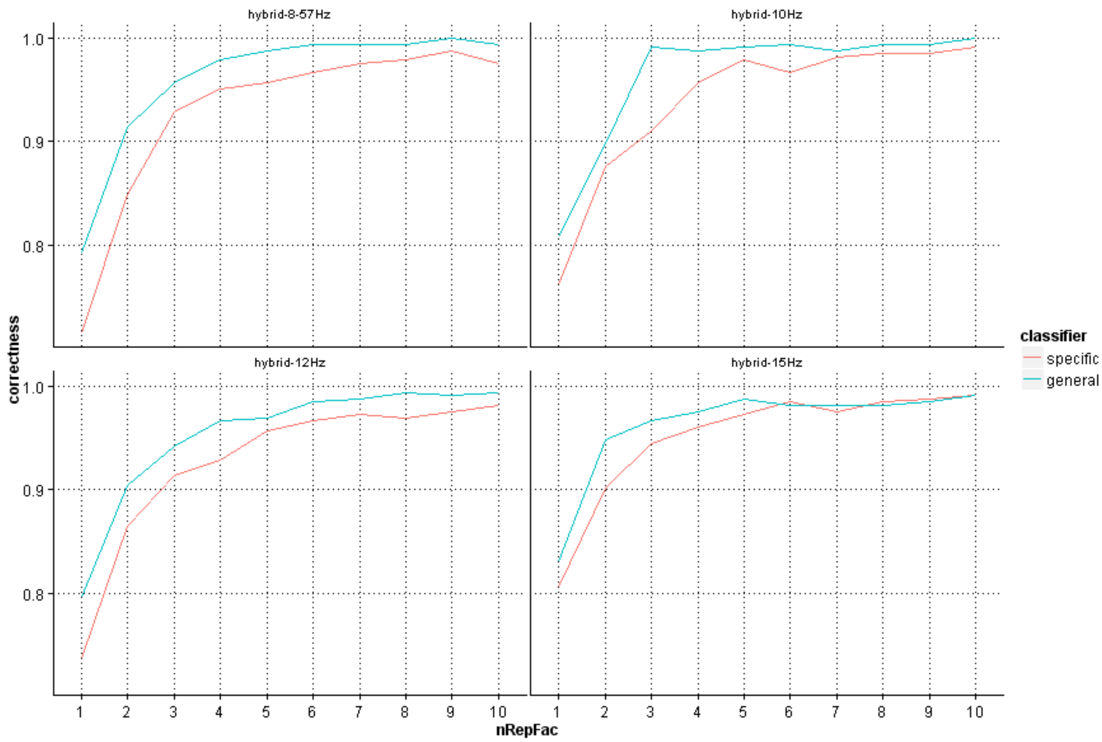

Figure 7: Accuracy of oddball ERP detection (subject mean) with respect to the number of repetitions considered for each experimental condition and classifier.

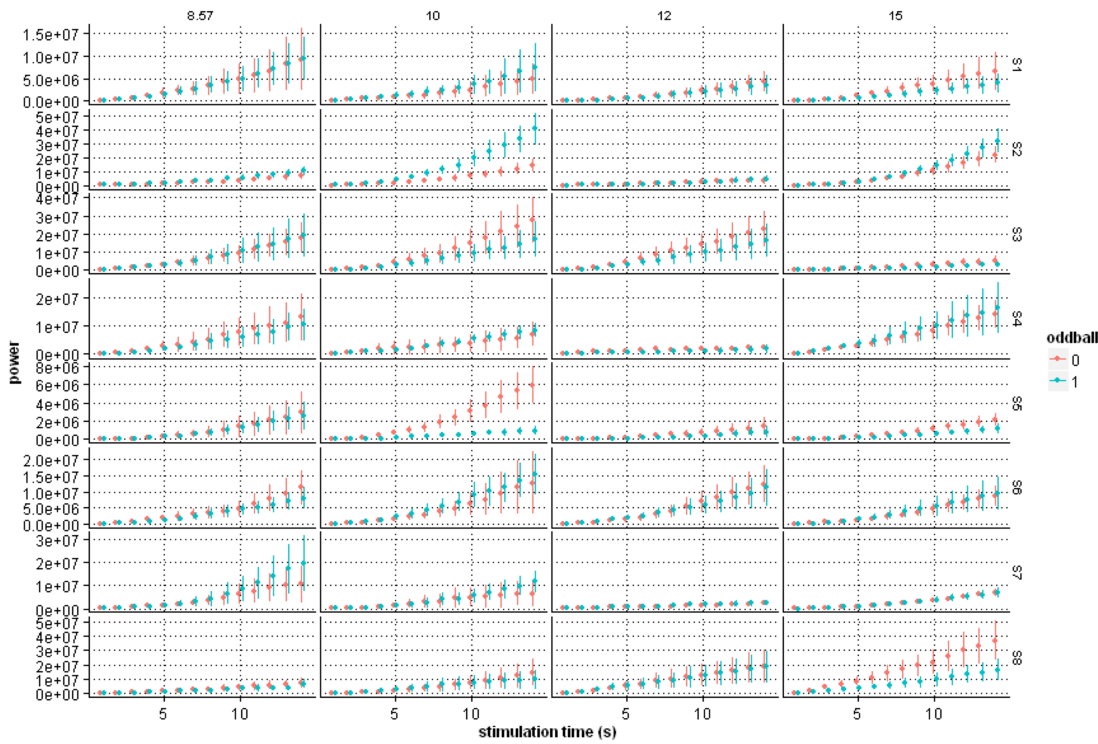

Figure 8: Power of the EEG signal recorded at Oz during the SSVEP stimulation with respect to the stimulation time for each subject, stimulation frequency and oddball condition. The values are averaged over the 12 trials performed by each all subject in every conditions and the bars reprensent the 95% confidence intervals.

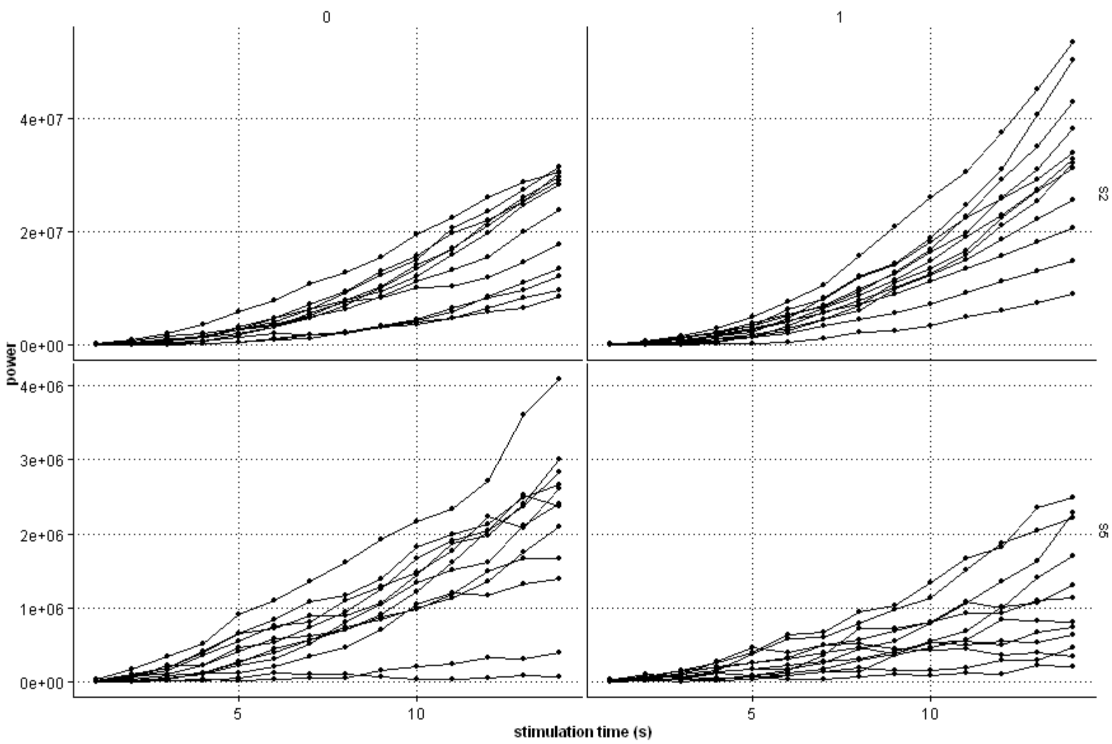

Figure 9: Power of the EEG signal recorded at Oz during the SSVEP stimulation with respect to the stimulation time for subjects S2 and S5, with a 15 Hz stimulation frequency with and with the oddball stimulation. In each panel, all 12 trials are represented.

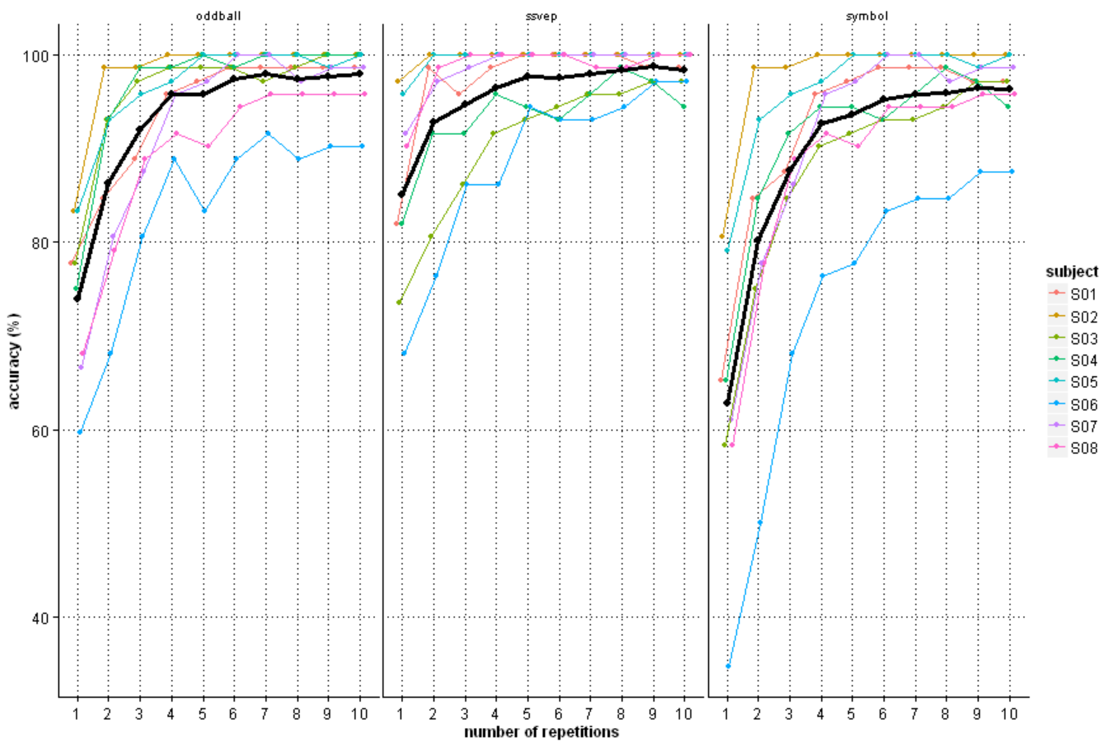

Figure 10: Detection accuracies with respect to the number of repetitions considered for each subject for the oddball ERP (left), SSVEP frequency (middle) and target symbol (left). the black lines represent the average over subject. One repetition of the stimulation cycle lasted for 1.5 s, the stimulation duration for a number n_r of repetitions is thus $1.5 \times n_r$ seconds.

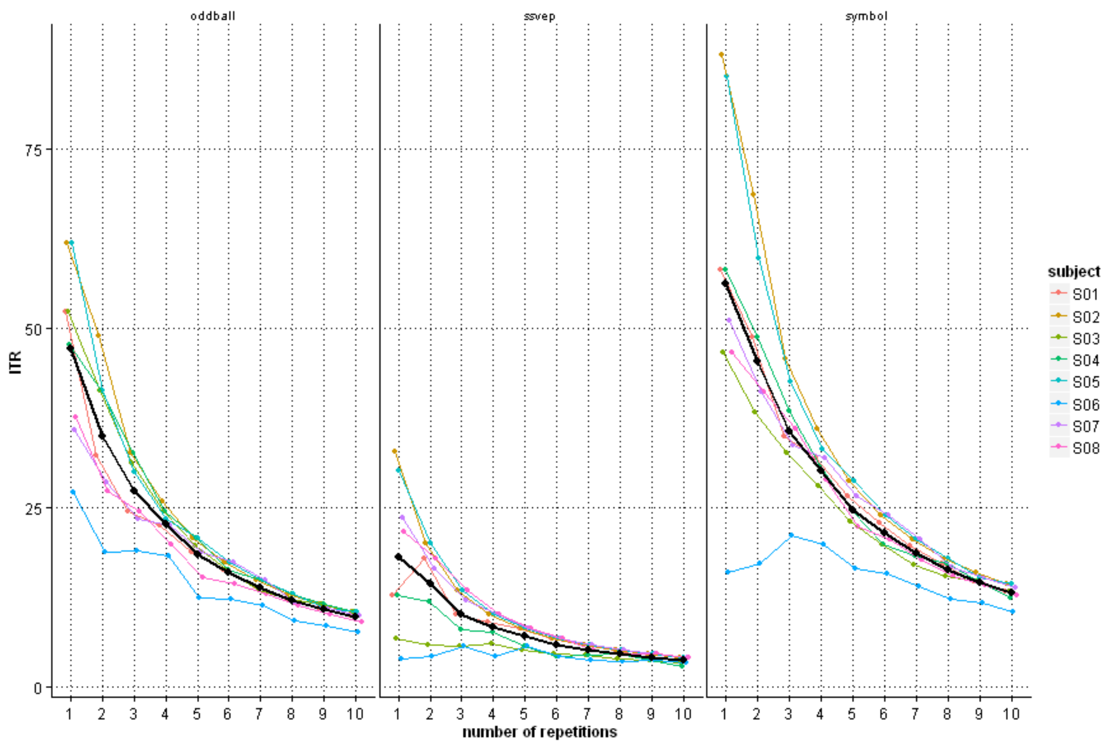

Figure 11: ITR values with respect to the number of repetitions considered for each subject for the oddball ERP detection (left), SSVEP frequency detection (middle) and target symbol detection (right). the black lines represent the average over subject. One repetition of the stimulation cycle lasted for 1.5 s, the stimulation duration for a number n_r of repetitions is thus $1.5 \times n_r$ seconds.

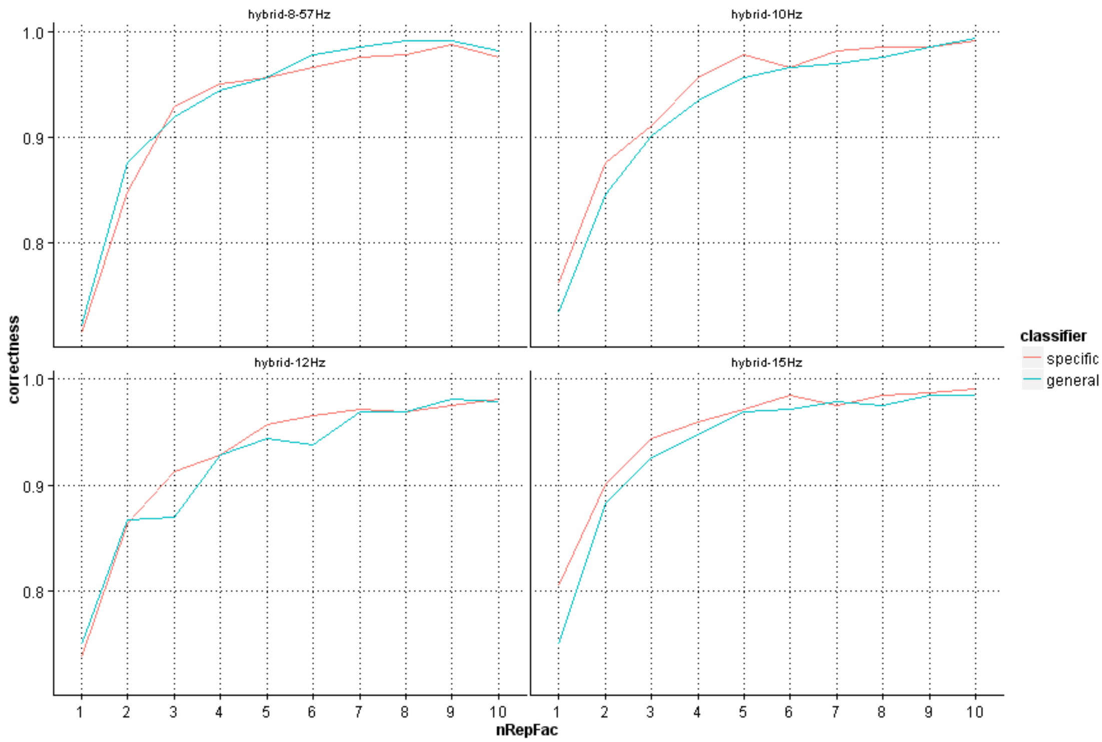

Figure 12: Accuracy of oddball ERP detection (subject mean) with respect to the number of repetitions considered for each experimental condition and classifier.