SSVEP-based BCIs: study of classifier stability over time and effects of human learning on classification accuracy

Alban Duprès, François Cabestaing, José Rouillard

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A. Duprès*, F. Cabestaing**, J. Rouillard***

* LAGIS Laboratory, Lille1 University,
Villeneuve d'Ascq, FRANCE, alban.dupres@univ-lille1.fr
** LAGIS Laboratory, Lille1 University,
Villeneuve d'Ascq, FRANCE, francois.cabestaing@univ-lille1.fr
*** LIFL Laboratory, Lille1 University,
Villeneuve d'Ascq, FRANCE, jose.rouillard@univ-lille1.fr

Abstract

Brain-computer interfaces (BCI) based on steady-state visual evoked potentials (SSVEP) enable a user to control an application by focusing his/her attention on visual stimuli blinking at specific frequencies. This technique of interaction can enable people suffering from severe motor disabilities to improve their quality of life through regaining a partial autonomy. According to literature, each usage session of a SSVEP-based BCI integrates a calibration phase aimed in particular at computing classifier's parameters. Our objective is to evaluate if the same parameters could be used during several sessions, in order to avoid performing systematically a calibration phase, which is very restrictive for the user. To do so, we analyze stability of classification results over time. On the other hand, the data acquired during our experiments were used to study the possible effects of human learning on interface performance and to confirm or not the state of the art knowledge on this subject. According to literature, SSVEP-based BCIs work well from the first use and their performances do not improve with subject's experience.

Key words

Brain-computer interfaces (SSVEP); learning; evaluation; classifier.

1. Introduction

A BCI is a system that establishes a direct communication link between a device (robotic arm, wheelchair) or a computer and the user's brain, without involving nerves and peripheral muscles. This kind of interface could be useful for patients suffering from a degenerative disease (DMD, Duchenne Muscular Dystrophy or amyotrophic lateral sclerosis) or from spinal cord injuries, allowing them to recover a partial autonomy and to improve their quality of life.

Other proven technologies have preceded BCI in this field: eye-tracking [1], head-tracking [2], interfaces based on electromyography [3] or electro-oculography [4], trackball [5], joystick, contactors, voice recognition systems [6]. Related work described in literature seem to indicate that these techniques enable, for now, a more reliable and faster control compared to BCI approaches [7], [8].

It is therefore legitimate to give priority to these techniques, in the field of handicap palliation, instead to BCI. Nevertheless, for severely disabled patients, the previously mentioned techniques suffer from some limitations that BCI does not have. The main one is the necessity to keep a residual muscular activity, even minimal. Some people suffering from a locked-in-syndrome are unable to interact with a computer or a machine through these standard interfaces. Moreover, even for some people able to use common assistive devices, BCI could be beneficial for some applications. For instance, wheelchair steering is more intuitive and better adapted with a movement imagination based BCI [9] than with a eye-tracking system.

For people who are completely paralyzed, but with intact cognitive capabilities, BCI is nowadays considered as the only technique that can restore an effective communication link with the environment. That is why BCI can play a significant role in the field of severe motor handicap assistance and should be not neglected for the support of highly handicap patients. A brain-computer interface relies on six functional stages (see figure 1):

1) cerebral activity monitoring. More or less invasive acquisition systems are available to perform this task: electroencephalography (EEG), electrocorticography [10], direct neural interface [11], magneto-encephalography. For our study, we have used EEG. Electrical brain activity was recorded thanks to electrodes connected to the scalp.

2) signal processing. This step aims at removing noise from signals. Noise can come from several sources: radiation from electrical power network (50 or 60 Hz), muscular or ocular activity, background cerebral activity (α rhythm), etc. In the case of SSVEP, some frequencies of the α rhythm can match those of the visual stimulation patterns. The noise removal step is essential in order to be able, in a following stage, to highlight the relations between the electro-physiological patterns and a specific brain response.

3) features extraction, which consists in transforming filtered signals into feature vectors. Feature vectors aggregate relevant values that are later used for mental state classification. For instance, we can define the signal power in a particular frequency band as a feature value.

4) classification, which determines the class to which the measured mental state belongs, according to the values of associated feature vectors. Classification can be performed online to control the application, but also offline to assess classifier performance.

5) computer control, which is performed when system has identified, thanks to the classification step, the mental task realized by the subject. To each mental state is associated a different command, either in a fixed manner, or in relation to the current context.

6) feedback, which enables the user to know how the system has interpreted his mental state.

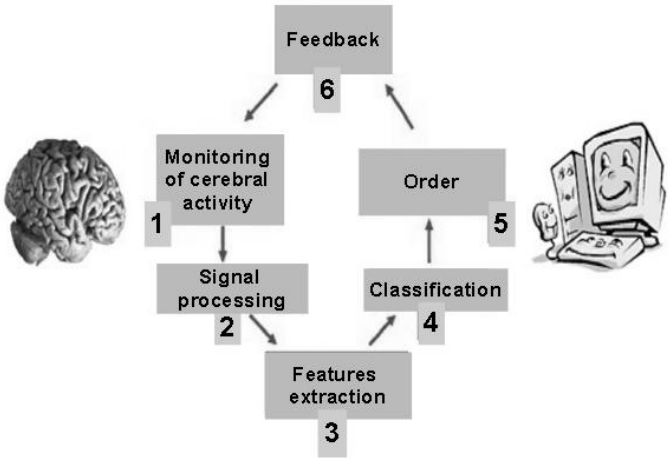

Figure 1: Six steps involved in BCI performing (source [12]).

The BCI is called asynchronous (or self-paced) when electrophysiological patterns are triggered by the user himself/herself and synchronous when patterns are triggered by an external stimulation. The most studied asynchronous BCI rely on the execution by the user of mental tasks such as movement imagination (MI) or continuous control of slow cortical potentials. Synchronous BCI mainly use two categories of stimuli induced cerebral patterns: steady-state visual evoked potentials (SSVEP) and transient evoked potentials (P300). [13] presents a detailed description of BCI systems and of the various usage paradigms. In this paper we will focus our attention on SSVEP-based BCIs.

SSVEP is a type of evoked potential which appears over the occipital lobe in response to a repetitive visual stimulation. Occipital lobe is the integration center of visual information. This evoked potential signal oscillates at the same frequency as the stimuli. Therefore, to detect this very specific ”mental state” in the signals, one only needs to filter them using pass-band filters. Thanks

to its frequency, the stimulus observed by the user is determined, and the interface can trigger the associated command on the computer.

The use of a SSVEP-based BCI needs a first calibration stage in order to adjust the classifier to user's specificities. Calibration stage requires a high concentration level from the user in order to obtain a robust classifier and to maximize system performances. Usually, the calibration stage is performed at the beginning of every session, resulting in additional fatigue, boredom and waste of time for the user. To our knowledge no study seems to have addressed this redundancy issue of the calibration phase. That is why we decided to study classifier stability over time: if the calibration performed during one session remains valid for the next session, one can decide to skip the calibration stage.

So, the aim of the first part of the work presented in this article is to assess if classifier's coefficients, specifically computed for a user, can be reused by the same person several days after their computation, in order to reduce the number of calibration stages and so limit drawbacks related to this step.

According to literature, SSVEP-based BCI perform correctly at the first use [14], [15]. No performance improvement seems to be observed with the increase of user experience, unlike with other paradigms such as movement imagination [16] or continuous control of slow cortical potentials [17] for which several weeks or months are required to control reliably an application. Therefore, benefiting from recorded data used to answer to the first problematic, we study human learning effects on SSVEP-based BCIs' performances in order to confirm or not the results described in the literature.

In the last part of the related work, we assess, based on data recorded on healthy people, if SSVEP-based BCIs can be pertinent for disability compensation. The objective is to test if SSVEP can challenge other paradigms, knowing that usefulness of MI as well as P300 has been already shown in [18] and [19] in the field of assistance to disable people.

2. Data acquisition and experimental protocol

The experiment was realized by 16 healthy subjects (12 men and 4 women) aged between 20 and 52 years old. Subjects' approval was verbally required and they were informed of the experiment content and the possibility to stop it at any time. Two of them (subjects 9 and 12) had previously used a SSVEP-based BCI. All subjects had normal or corrected to normal vision. Participants were asked to seat comfortably in an armchair in order to have them relaxed and to limit muscular artifacts. They were also asked to avoid blinking their eyes during the experiment in order to prevent recording of ocular artifacts. Subjects were facing the computer monitor, at a distance of 70 cm from their eyes, and room lighting was decreased to improve the quality of the SSVEP signal. Indeed, our first attempts in broad daylight rapidly showed that the SSVEP amplitude was not large enough to allow a correct discrimination of the frequencies in the signals, resulting in an inaccurate control of the system.

Subjects were wearing an electrode cap (GAMMAcap, g.tec), with Ag/AgCl electrodes located according to the international 10/20 system [20]. Four mono-polar channels were recorded from the occipital lobe: O_z, O_1, O_2 and PO_z with an electrode clipped on the right ear as a reference and another one on the forehead as mass. A gel was applied between skin and electrodes to increase conduction of electrical signal. Signals were amplified, band-pass filtered between 0.1 and 100 Hz (50 Hz was eliminated to remove artifacts caused by the power electrical network) then sampled at the frequency Fe = 512 Hz.

The recording system was composed of a physiological signals amplifier with 16 channels (g.USBamp, g.tec) and a DELL laptop using windows XP operating system. An additional computer screen was used to display stimuli. All the displays and processing presented in the article were performed by the OpenViBE (openvibe.inria.fr) software, which allows one to control online signal acquisition, signal processing and orders sending for application control.

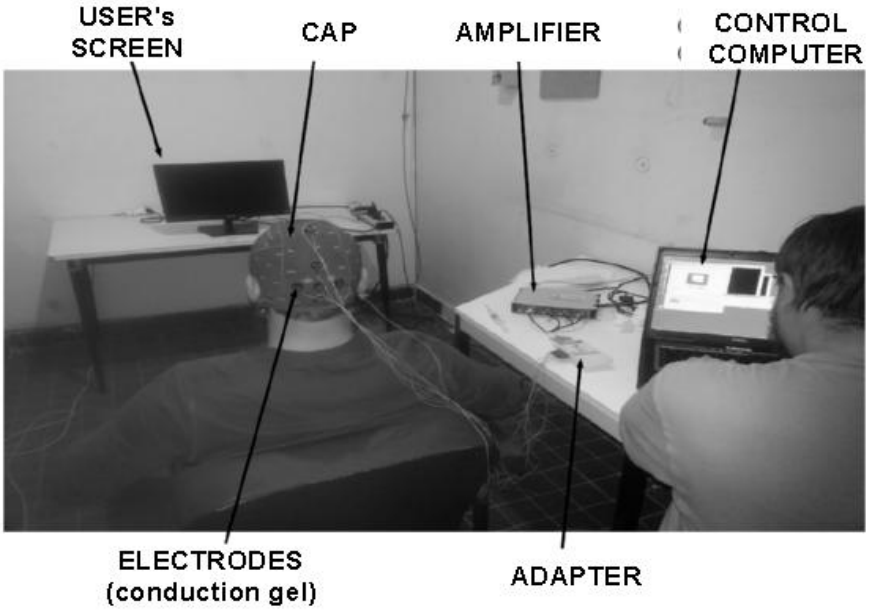

Figure 2: BCI experimental setup.

Figure 2 shows our experiment room and devices used for these BCI experiments. Each subject was asked to perform three sessions during a period of ten days. The second and third sessions occurred respectively two and ten days after the first one, as shown in table I. The first session was composed of a calibration phase followed by an online phase, during which the subject was controlling a simple shooting game. Sessions 2 and 3 were composed of 3 phases: a first online phase using the classifier trained during the first session, then a calibration phase followed by a second online phase using a newly trained classifier. Each session lasted from 30 to 45 minutes according to the time needed by the user to finish the game.

Session 1 (Day 0)	Session 2 (Day 2)	Session 3 (Day 10)
C_1 A_1	A_1' C_2 A_2	A_1'' C_3 A_3

Table I: Contents of each session. Letters C and A mean respectively calibration and application. A_1' andA_1'' correspond to the application performed online during sessions 2 and 3, using classifier trained during the first session.

The calibration phase enables one to compute classifier's coefficients used for online interaction with the application (online phase). Data recorded during this phase are also used to assess offline the performance of classifiers. In this paper, we use the adjective "offline" only when the classifier is assessed on pre-recorded data and not on data acquired during the same session. For the calibration phase, four targets were displayed on a screen. Three of them blink at a constant frequency, whereas the last one remains fixed, as shown in figure 3. The stimulation frequencies of the targets were 6, 10 and 15 Hz, which had been selected since they are submultiples of 60 Hz, which corresponds to the screen refresh rate. Targets were chosen white on a black background in order to increase the contrast. This enables to further stimulate the user's retina and so to increase SSVEP amplitude. Subjects were asked to focus their visual attention on specific target indicated by a yellow arrow. Each trial lasts for 7 seconds followed by a rest time of 4 seconds. A total of 32 trials (8 by target) is realized by each subject.

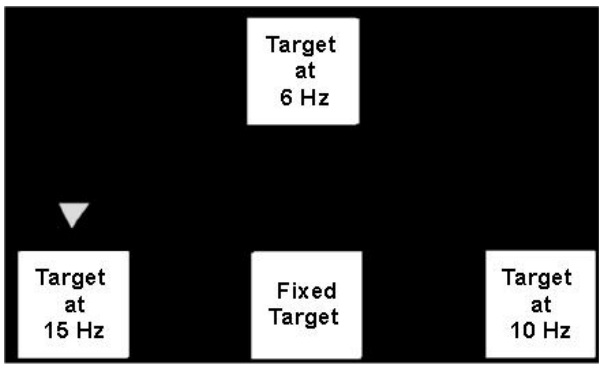

Figure 3: Calibration phase.

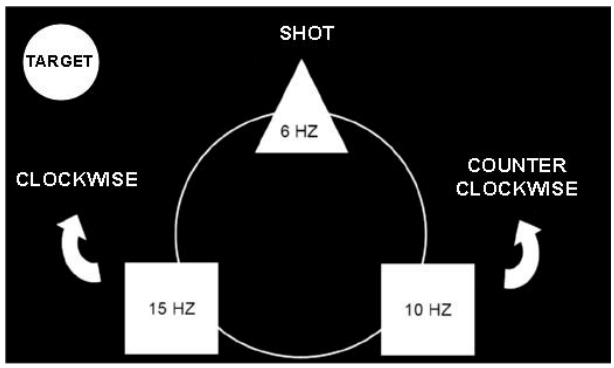

Figure 4: Online phase: shooting game.

During the online phase the user plays to a simple game, already included in the OpenViBE software suite. The goal is to make a ”spaceship” shoot on targets. Targets are represented by full circles, whereas the ”spaceship” is sketched by an empty circle on which are disposed equidistantly 3 stimuli, 2 squares and a triangle as shown by figure 4. By focusing his/her gaze on the left or right square, the user controls the rotation of the ”spaceship” respectively in the clockwise or counter-clockwise directions. By focusing his/her gaze on the triangle, the user can shoot in order to reach a target which disappears and reappears at a random position on the screen. The game ends when 8 targets have been shot.

3. Signal processing and classification

This part covers all signal processing and classification techniques. Signal processing allows us to remove as many artifacts as possible from the signals in order to keep only the task related information. Classification step uses this information to identify the cerebral patterns specific to the SSVEP control mode and to send orders to an online application, such as the shooting game.

Literature has shown the efficiency of spatial processing with CSP filters [21] and LDA classifiers [14] for a binary classification issue in the field of SSVEP. That is why we decided to use these techniques in our study. Their calibration is specific to each user and therefore requires at some point a set of calibration data. The first processing step consists in filtering raw signals around each stimulation frequency (6, 10 and 15 Hz) with a 4^{th}-order Butterworth band-pass filter. The actual band-pass around each frequency is set to $\delta = 0.25$ Hz. The filtered signals are then used to optimize CSP (Common Spatial Pattern) filters. A window of interest of 7 seconds is extracted in the signals, beginning 1 second after the start of each trial. Therefore, we record 8 learning windows (or data packets) for each stimulation frequency, including the null frequency (corresponding to the absence of stimulation). For training a processing chain (CSP and LDA classifier) for each frequency, the data of the learning set are then separated into two classes. One class corresponds to the frequency of interest (for instance 10 Hz) and the other one to all other frequencies. First, a spatial filter is specifically calibrated for each stimulation frequency.

Once the spatial filters have been adjusted, they are used to compute feature vectors that feed the LDA (Linear Discriminant Analysis) classifiers. Thus, a LDA classifier is trained specifically for each stimulation frequency. At the output of the CSP filters, the data forms a matrix of 2 column and N lines, with N the number of samples included in the 7 seconds time window, i.e. $N = Fe \times 7$. Data are then split again into two classes according to the frequency class they belong to and used to train the classifier. For instance, if we train the classifier used to detect a stimulation at 6 Hz, data packets recorded during the 6 Hz stimulation belong to the first class and those recorded during the other stimulation periods belong to the second class. Then, for each packet of each class, we extract overlapping windows with half-second duration every one tenth of a second. We get 66 learning windows for each packet, rather than 70, since the last windows do not fit entirely in the time interval. A learning window is therefore a matrix of 2 columns (signals filtered by the CSP filters) and l lines, with $l = Fe \times 0.5$ the number of samples recorded during half a second. Values included in each window are squared then averaged on each column, such as each

packet P ($P \in \mathbb{R}^{66x6}$) is composed of 66 pairs of feature values (X, Y). Finally, the values X and Y are log transformed into log(X + 1) and log(Y + 1) before feeding the classifier.

OpenViBE software uses a 10-fold cross-validation method to train the classifiers. Feature values are split into 10 groups regardless of their class. The classifier parameters are adjusted with the data of 9 groups, and then assessed on the data of the last one. This is repeated 10 times in order to assess the classifier on each group. The classifier with the highest performance is kept for the online phase. During the online phase, CSP filters and LDA classifiers analyze continuously the signals recorded during the last second, with a shift of 0.1 second. Classifier's output is an index computed from the distance between the feature vector and the point, straight line, plane or a hyperplane considered as separating the two classes. We get an index value for each classifier, i.e. for each stimulation frequency. Online decision is made by an automatic vote selecting the classifier with the maximum output.

To calibrate the classifier offline, we use a slightly different approach. For each frequency, we remove the most outlying packets, i.e. packets with an average center point located on the wrong side of classifier's decision frontier. Thus, coefficients are computed from the 31 remaining packets, 7 belonging to the class of frequency for which we compute the classifier and 24 belonging to other classes. In order to evaluate intra-session performance, we split the data used for classifier training again into 2 groups. One group is used to adjust the classifier parameters and the other one to assess its performances. To assess inter-session performances, we apply directly the main classifier to all data of other sessions.

4. Results

This part presents online and offline average performances obtained from all participants during three sessions. Time (seconds) and area under the curve (AUC) correspond respectively to online and offline performance indices. Offline performance index is defined by υ value, with $0 \leq \upsilon \leq 1$, such as classifier performance is proportional to υ value. A classifier with a value $\upsilon = 1$ is perfectly accurate, and with a value of $\upsilon = 0.5$ it gives random results. Thus, υ allows us to compare performances obtained under different conditions and to answer the question related to classifier stability. Given that sample size is lower than 30, performances are compared from a Wilcoxon non-parametric test, with a risk set to 5%.

4.1. Offline classification performances

Figure 5a compares offline performances of classifier 1 (classifier computed with data recorded at the first session) on data of session 1 (C_1) with its performances on data of session 2 (C_1') and 3 (C_1'').

Figure 5b compares offline performances of classifier 1 on data of session 2 (C_1') and 3 (C_1'') with respectively performances of classifier 2 and 3 (classifier computed respectively with data recorded at session 2 and 3) on data of session 2 (C_2) and 3 (C_3).

Figure 5c compares offline performances of classifier 1 on data of session 1 (C_1) with respectively performances of classifier 2 and 3 on data of session 2 (C_2) and 3 (C_3). All presented performances correspond to average performances of all subjects.

To study classifier stability over time we perform two statistical tests. The first one, as shown in figure 5a, compares performances between sessions 1 and 2 then between sessions 1 and 3. This comparison takes into account performances of one classifier (classifier 1) assessed on calibration data recorded at intervals of several days. Thus, we assess classifier reliability at different times and under different experimental conditions. In fact, different parameters vary from one session to another: electrodes positions, user motivation and fatigue, etc.

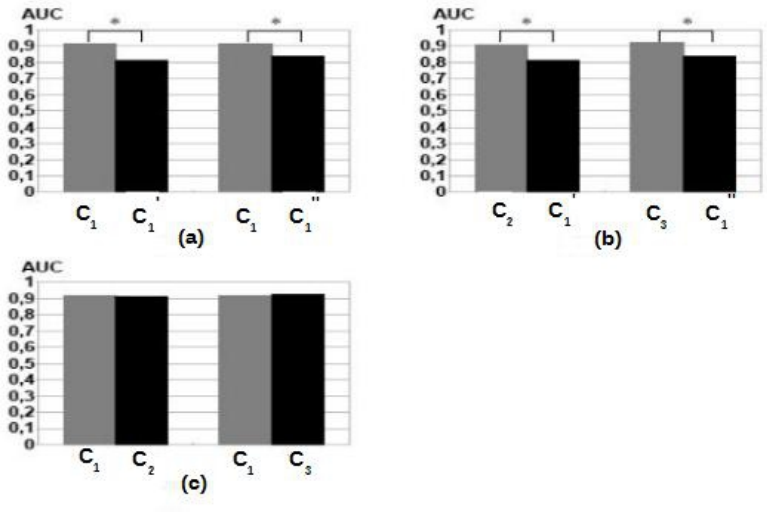

Figure 5: Histograms for comparison of offline performances
of different classifiers on various datasets.

A Wilcoxon test indicates significant difference between classifier performances on data of sessions 1 and 2 (p-value = $3.051.10^{-5}$). A significant difference is also observed between classifier performances on data of sessions 1 and 3 (p-value = $9{,}15.10^{-5}$). This result is supported by a second statistical test, see figure 5b, which compares performances of classifier 1 with those respectively of classifier 2 and 3 on data of sessions 2 and 3. The idea is to compare performances of a former classifier with those of a newly computed classifier. In this case classifiers are compared on the same calibration data and so under the same experimental conditions. A Wilcoxon test indicates a significant difference between performances of classifiers 1 and 2 on data of session 2 (p-value = $3.051.10^{-5}$) and between performances of classifiers 1 and 3 on data of session 3 (p-value = $3.051.10^{-5}$).

Finally, to study human learning effects on BCI performances, we compare performances between session 1 and session 2, then between session 1 and session 3 (see figure 5c). These are performances of different classifiers assessed on different calibration data. Performing a Wilcoxon test, we do not observe a significant difference between performances of classifier 1 and 2 respectively on data of sessions 1 and 2 (p-value = 0,175), then between performances of classifiers 1 and 3 respectively on data of sessions 1 and 3 (p-value = 0,632).

4.2. Online classification performances

Figure 6a compares online performances of classifier 1 during session 1 (A_1) with its performances during session 2 (A_1') and 3 (A_1'').

Figure 6b compares online performances of classifier 1 during session 2 (A_1') and 3 (A_1'') with respectively those of classifiers 2 and 3 during session 2 (A_2) and 3 (A_3).

Figure 6c compares online performances of classifier 1 during session 1 (A_1) with respectively performances of classifiers 2 (A_2) and 3 (A_3) during sessions 2 and 3.

All presented performances correspond to averaged performances of all subjects.

Results presented in figure 6 do not consider subjects who could not control the application. In fact, two subjects (subjects 3 and 5) were not able to control the application whatever classifiers and sessions. Two other subjects (subjects 12 and 13) had no control on the application during sessions 2 and 3, using classifier 1. Finally, a last subject (subject 14) had no control on the application during session 3, using classifier 1.

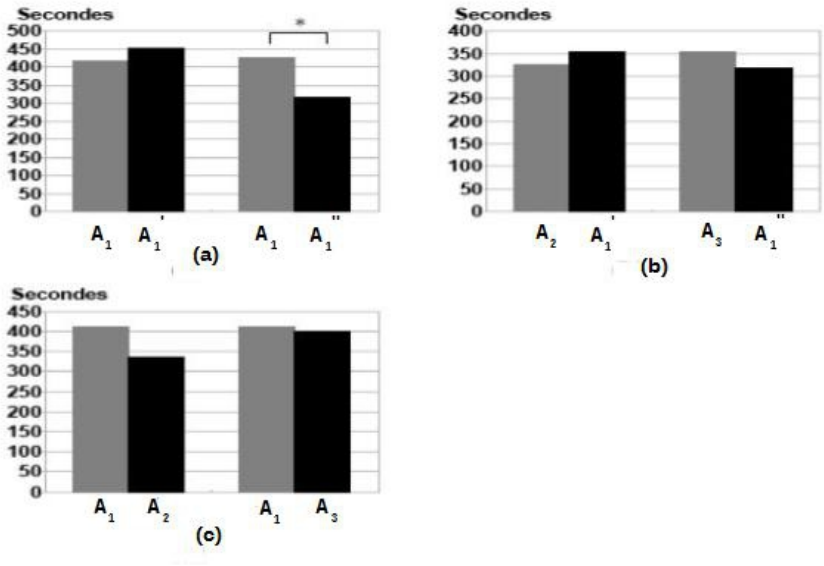

Figure 6: Histograms for comparison of online performances of several classifiers for different sessions.

To study classifier stability over time we performed the same statistical tests as in section 4.1. In a first step, we compare performances between sessions 1 and 2 then between sessions 1 and 3 (see figure 6a). We assess classifier (classifier 1) reliability at different times and under different experimental conditions. A Wilcoxon test does not indicate a significant difference between performances obtained during session 1 and during session 2 (p-value = 0.339). Nevertheless we observe a significant difference between performances obtained during session 1 and during session 3 (p-value = 0.0136). This result is confirmed by a second statistical test which compares results observed during the two online phases of sessions 2 and 3 (see figure 6b). Thus, we compare online performances of the first classifier with those of newly computed classifiers. In this case classifiers are assessed under the same experimental conditions. A Wilcoxon test does not indicate a significant difference between performances of classifiers 1 and 2 during session 2 (p-value = 0.51) and between performances of classifiers 1 and 3 during session 3 (p-value = 0.365).

Finally, to study the effect of human learning on BCI performance, we compare performances between sessions 1 and 2, then between sessions 1 and 3 (see figure 6c). These are performances of different classifiers assessed in different experimental conditions. The Wilcoxon test shows that there is no significant difference between performances of classifier 1 and 2 respectively during sessions 1 and 2 (p-value = 0.104), nor between performances of classifiers 1 and 3 respectively during sessions 1 and 3 (p-value = 1).

5. Discussion

First of all, we focus our attention on the possible effect of human learning on BCI performances. Statistical tests do not show significant differences between offline performances obtained with different classifiers computed at different sessions (see figure 5c). We note similar results concerning online performances (see figure 6c). This suggests that human learning has no effect on classifier performances. In fact, results obtained offline or online do not improve significantly from one session to another, whereas subjects acquire more and more experience with time. Moreover, we do not notice an improvement of online or offline results obtained by subjects who already had an experience with SSVEP-based BCI (subject 9 and 12) compared to other subjects' results.

We notice that all subjects, except subjects 3 and 5, were able to finish the game in a satisfying time interval (≈13 minutes) when they used a newly computed classifier. This tends to prove that SSVEP-based BCI is efficient at first use. Nevertheless, as for other paradigms (MI, SCP), there are users for which the interface does not work even after several sessions, such as for

subjects 3 and 5. We frequently find in literature the word “illiteracy” to characterize this phenomenon [22]. Nevertheless, a subject identified as “illiterate” for a paradigm is not necessary illiterate for another. That is why it is interesting to propose to participants a “hybrid interface”, which associates several types of BCI [23] or a BCI with another control channel [24].

We can also focus our attention on the analysis of classifier stability. Statistical tests performed with offline results (see section 4.1) suggest a stability of the classifier over time. Indeed, we note a significant decrease of performance from the same classifier assessed on data of different sessions (see figure 5a). This finding is similar when we compare performances of a former classifier with those of a new one assessed on data of the same session (see figure 5b). Nevertheless, those results are not confirmed by online results (see figures 6a and 6b). In fact, statistical tests do not seem to show significant differences between these configurations. An improvement of results is even observed (see figure 6a). Online performances of classifier 1 seem to have improved from session 1 to session 3. Online and offline results are contradictory. Offline results seem to decline when classifier is reused on other calibration data. However, this degradation of offline results does not seem to affect online results because they remain constant and even improve in one case. This can be explained by the fact that online performances do not depend only on classifier reliability but also mainly on the playing strategy adopted by user. Indeed, we can notice an inertia phenomenon during the game: the “spaceship” continues its rotation for a while after the end of the visual stimulation. This can be explained by the fact that neurons of the occipital lobe remain activated for a while after the end of stimulation. This inertia phenomenon prevents the user from correctly controlling the application. Online performances depend mainly on his/her capacity to anticipate this phenomenon.

All these results suggest that a classifier can be re-used several days after its calibration phase despite a slight decrease of its offline performances. Nevertheless, it is important to mention that two subjects (subjects 12 and 13) did not succeed to re-use online the classifier and a last one (subject 14) did not succeed to re-use it during the last session. Moreover the experiment has been performed over ten days, so we can not conclude on classifier reliability beyond this period. Finally, our study does not consider men/women potential disparities.

6. Conclusion

SSVEP-based BCI have the advantage to perform well from the first use [14], [15]. No long and tedious learning stages from user is necessary contrary to slow cortical potentials [17] or movement imagination [16]. Indeed these two types of BCI need an strong cognitive process to learn controlling the cerebral patterns specific to each mode, whereas SSVEP mode involves only a perceptual process. The subject only needs to focus his/her visual attention on a particular stimulus which excites his/her retina and induces a SSVEP over the occipital lobe. So we understand by the nature of its mechanism that SSVEP paradigm works well without human learning. However, one can wonder if, with the training at performing constantly the same experiment, a user reaches consciously or not to further focus on stimuli and so to get better results. Data we have collected and processed do not seem to indicate a significant improvement of performances with increase of subject’s experience. These results tend to confirm those of the literature.

The high visual and cognitive concentration required from the user in the SSVEP paradigm, in particular during the calibration stage in order to maximize classifier performances, induces a early fatigue and may cause some weariness. That is why our study addresses classifier stability over time, to check if it is possible to avoid introducing a calibration stage at the beginning of each session. Our results tend to indicate a decrease of offline performances for the same classifier from one session to another. However, it does not affect online performances as soon as the offline performance decrease does not exceed a threshold (about 80%), which allows the user to keep a proper control on the application. This tends to show that a classifier can be re-used without performing a new calibration phase.

Finally, our results tend to show that the SSVEP paradigm enables to get, for some subjects,

a quick and satisfying control of the interface for novice users. Nevertheless, even if constraints can be decreased by avoiding extra calibration stages, this paradigm remains in the long run very stressing for the user. Indeed, we noticed for some people a phenomenon of eye blinking and eye tingling caused by stimuli. If this paradigm is binding for healthy people after few minutes (≈ 30 min) of use, we can deduce that it is not suitable to a context of an extended use as will required for disabled people. SSVEP mode can be an interesting strategy, in a first time, to allow patients to gain quickly autonomy. But in a second time, a gradual shift to another paradigm, such as MI, will be more judicious. SSVEP mode can be used in a hybrid BCI wherein it do not represent main component of the interface. This will limit SSVEP constraints while keeping its advantages.

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