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2015 J. Neural Eng. 12 056007

(http://iopscience.iop.org/1741-2552/12/5/056007)

IOP Publishing Journal of Neural Engineering

J. Neural Eng. **12** (2015) 056007 (10pp) doi:10.1088/1741-2560/12/5/056007

Attention-level transitory response: a novel hybrid BCI approach

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Received 29 April 2015, revised 8 July 2015
Accepted for publication 20 July 2015
Published 13 August 2015

Abstract

Objective. People with disabilities may control devices such as a computer or a wheelchair by means of a brain–computer interface (BCI). BCI based on steady-state visual evoked potentials (SSVEP) requires visual stimulation of the user. However, this SSVEP-based BCI suffers from the 'Midas touch effect', i.e., the BCI can detect an SSVEP even when the user is not gazing at the stimulus. Then, these incorrect detections deteriorate the performance of the system, especially in asynchronous BCI because ongoing EEG is classified. In this paper, a novel transitory response of the attention-level of the user is reported. It was used to develop a hybrid BCI (hBCI). *Approach.* Three methods are proposed to detect the attention-level of the user. They are based on the alpha rhythm and theta/beta rate. The proposed hBCI scheme is presented along with these methods. Hence, the hBCI sends a command only when the user is at a high-level of attention, or in other words, when the user is really focused on the task being performed. The hBCI was tested over two different EEG datasets. *Main results.* The performance of the hybrid approach is superior to the standard one. Improvements of 20% in accuracy and 10 bits $\min^{-1}$ are reported. Moreover, the attention-level is extracted from the same EEG channels used in SSVEP detection and this way, no extra hardware is needed. *Significance.* A transitory response of EEG signal is used to develop the attention-SSVEP hBCI which is capable of reducing the Midas touch effect.

S Online supplementary data available from stacks.iop.org/JNE/12/056007/mmedia

Keywords: brain–computer interface (BCI), attention-level transitory response, steady-state visual evoked potential (SSVEP), false positive, midas touch effect

(Some figures may appear in colour only in the online journal)

1. Introduction

A brain–computer interface (BCI) is a system that helps handicapped people to control a device or a computer using only their own brain signals. A BCI usually acquires these brain signals as electroencephalographic (EEG) signals. Then, according to the nature of the EEG signal, different BCI paradigms like motor-imagery, P300 or steady-state visual evoked potentials (SSVEP) are established. Particularly, SSVEP are evoked responses, arising mainly in the visual cortex, induced by flickering visual stimuli. They are periodic, with a stationary distinct spectrum showing characteristic SSVEP peaks, remaining stable over time [1].

The main problem of SSVEP-based BCI is that the visual stimuli are always within the field of vision of the user. This is known as the 'Midas touch effect' [2]. Consequently, SSVEP could be detected by the BCI even when the user is not gazing at the stimulus and therefore, could lead to erroneous detections. Generally, this problem is faced by designing BCI with higher detection accuracy. However, this problem is particularly evident in asynchronous BCI approaches because the EEG is continuously classified. In some research studies, control and idle states are used to avoid the erroneous detections [3–5]. In those approaches, SSVEP are detected when the BCI is in control state; otherwise, in the idle state, SSVEP detection is not performed. In order to mitigate this SSVEP-based BCI problem, a hybrid approach could be used as well.

In order to reduce this SSVEP-based BCI problem, a hybrid BCI (hBCI) approach based on the attention-level of the user is proposed in this work. Following the state-of-the-art of hBCI and attention level are introduced.

1.1. hBCI approaches

A hBCI is composed of two BCIs, or one BCI and another system [6]. Therefore, BCI paradigms such as motor-imagery, SSVEP or P300 are used to compose an hBCI. In the motor-imagery paradigm, the user imagines the movement of a limb, usually, the right or left hand. The P300 potential is related to an infrequent stimulus (oddball paradigm). For example, a hBCI based on motor-imagery and SSVEP was presented in [7]. Another hBCI based on P300 and motor-imagery was proposed by [8]. The P300 speller combined with SSVEP blocking (when P300 is elicited), was implemented in [9]. On a different speller approach, P300 and SSVEP features were fused by means of probability estimation [10].

As already mentioned, a different kind of hBCI is obtained by combining EEG signals with other biomedical signals. For instance, an hBCI that combines electro-oculography with EEG signals is presented in [11]. Moreover, motor-imagery and electromyography were blended at different levels according to the remaining muscular activity of the user [12]. A recent review of hBCI systems is presented in [13].

As a counterpart, hBCI employs EEG signals from different regions of the brain. Therefore, electrodes placed over the motor cortex (such as C_3 and C_4 positions) are used for motor-imagery paradigm, electrodes on the visual-cortex (such as O_1, O_2 and O_z) are used for SSVEP paradigm and, P300 is measured over the central zone of the brain (close to C_z position).

In the current work, a novel approach is presented in order to reduce this SSVEP-based BCI problem (the Midas touch effect). Therefore, an hBCI based on SSVEP and the attention-level of the user is proposed. Moreover, this hBCI is based on EEG signals measured over the same region of the brain. This hBCI approach, as well as its application, has not been proposed in the bibliography heretofore, based on extensive research by authors.

1.2. Attention-level on EEG signals

The attention-level could be measured using the EEG signals. Consequently, another kind of BCI based on the attention-level has been proposed. For example, a video game controlled by using mental relaxation and concentration tasks has been previously reported [14]. Similarly, an archery video game has also been handled by the attention-level of the user in [15]. In fact, we have previously shown that the altitude of a ball in a glass pipe could be controlled by the concentration level of human subjects [16].

The attention control refers to the capacity of individuals to choose what they want to pay attention to and what they want to ignore [17]. Consequently, when a person pays attention to any stimulus, some changes should appear in the EEG signal. Individual visual environment is complex and attentive to some locations while ignoring others, yet it is crucial for reducing the amount of visual information to a manageable level. Lauritzen *et al* evaluate how attention changes the neural responses in visual areas of the brain [18]. They found that signals in areas V1, hMT+, and IPS were significantly higher during periods in which subjects detected the presence of a contrast increment target compared to periods in which contrast increments of the same amplitude were missed. Thut *et al* showed that the EEG activity in the alpha rhythm (8–13 Hz) is modulated by sustained voluntary attention [19]. These modulations typically take 400 ms to develop after the onset of a spatial cue and are generated by the brain when people are relaxing and/or having a quiet rest period [20]. On the other hand, beta rhythm (14–30 Hz) represents the excitement of the brain and theta rhythm (4–8 Hz) appears in deep relaxation, meditation, etc [21]. Then, the θ/β ratio indicates the attention-level so the smaller the ratio is, the higher the human alertness level is [22].

The attention-level of the user increases when the subject is gazing at a stimulus. Hence, the hypothesis of this work proposes that the attention-level could be measured along with the SSVEP on the same EEG channels. Interestingly, we found a transitory response of EEG signal. It appears when the person gazes at (and pays attention to) any stimulus. Thus, whether the person gazes at or glimpses the stimulus can be determined, which is crucial in asynchronous BCI approaches because the ongoing EEG is classified. These BCI approaches show more proclivities to misclassification since the user is paying attention to many things (the task being performed, the environment, etc) but not to the stimulus itself (but still within his visual field). The methodology proposed in this paper diminished the Midas touch effect on SSVEP-based BCI approaches since those erroneous detections could be reduced. Furthermore, it can be added to other SSVEP detection algorithms and consequently, to improve their performances. To the best knowledge of authors to date, this transitory response of EEG signal has not been reported in the bibliography.

2. EEG database

The authors previously acquired the EEG database used in this study [23]. Six volunteers (ages 32 ± 3; 1 F and 5 M) provided written consent to participate in the study. Each volunteer was seated in a comfortable chair in front of a monitor with four boxes on each side (10 cm $\times$ 2.5 cm), illuminated by high efficiency light-emitting diodes (LEDs) (figure 1). These LEDs flicker at 37, 38, 39 and 40 Hz for the box on top, to the right, then down and to the box on the left,

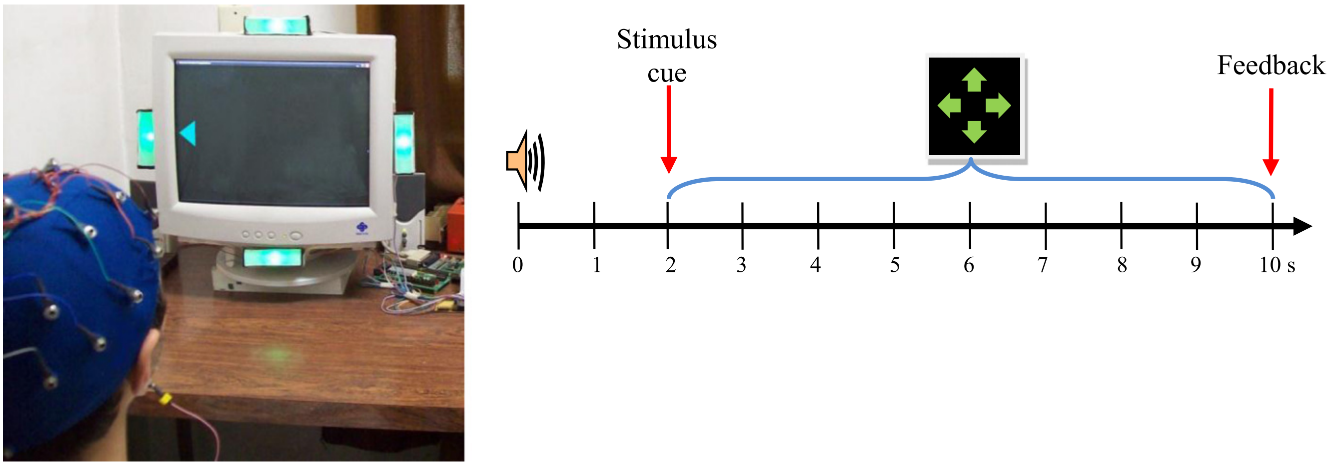

Figure 1. The interface with the stimuli (left). Timing scheme of each trial in BCI experiment (right), at $t = 2$ s a stimulus is indicated by an arrow on the screen.

respectively. The frequency of each LED was precisely controlled with an FPGA Xilinx Spartan2E.

Each trial lasts 10 s and begins with a beep alerting the volunteer. Two seconds later, a flickering stimulus is randomly indicated to the volunteer with an arrow on the screen. Feedback is presented at the end of each trial. All volunteers participated in four sessions; each session consisted of 20 trials, with only a few minutes between sessions. Additionally, a baseline EEG was acquired, where each volunteer was instructed to gaze at a point in the centre of the screen for 60 s, but not to focus on any stimulus (the stimuli were on).

The EEG was measured by six channels at O_1, O_z, O_2, P_3, P_z and P_4, referenced to F_Z and grounded at linked A_1–A_2. For on-line feedback, only O_1, O_z and O_2 channels were used. The EEG signals were sampled at 256 Hz. Analogical pass-band filters were set at 3 and 100 Hz and a notch filter for 50 Hz line interference was used. For each volunteer, a baseline EEG was acquired before the experiment, where the volunteers were asked to focus on a point in the centre of the screen for 60 s, but not to focus on any bar (which were on). This database is available from the authors free of charge, upon request.

3. Methods

In this section, the SSVEP detection method is briefly introduced followed by various methods for estimating the attention-level of the user. Finally, the proposed hBCI scheme is presented along with the methods used to validate the SSVEP detection.

3.1. SSVEP detection

The SSVEP were detected using the method proposed by the authors in [23]. The raw EEG was digitally filtered and the Fourier transform was applied to obtain the power at each stimulation frequency. Later, an SSVEP is detected when the maximum power is maintained for a period of time H. Threshold H is adjustable to the requirements of the user. In the current work, three threshold H were evaluated, namely $H = 1$ s, 1.5 s and 2 s respectively. This SSVEP-based BCI was successfully applied to control a mobile robot [24] and a robotic wheelchair [25] (achieving up to 72.5 bits min^{-1} in [25]).

Note that slight modifications from the proposed method were herein introduced. In [23], the SSVEP power was calculated on a bandwidth around the stimulation frequency and the classification process began at $t = 3$ s. In the current work, the SSVEP power was calculated at the same frequency as the stimulus and the classification process began at the same moment the stimulus was indicated ($t = 2$ s in figure 1). This last represents an unfavourable situation for classification purposes, since the user is not paying attention to any stimulus until $t = 2$ s (or maybe later). This condition might resemble an asynchronous BCI approach and consequently, other SSVEP could be detected. Thus, there is a greater probability of misclassification.

3.2. Attention-level detection

In order to detect the attention-level of the user some measures were proposed in this research. First, a common average reference filter was applied to the six EEG channels. Additionally, the EEG was filtered with a Butterworth low-pass filter with a cut off frequency of 45 Hz. Then, the power spectral density estimation is performed through the periodogram technique. Let $S(f)$ be the value of the periodogram at frequency f (in Hz):

$$S(f) = \frac{T_S}{N} \left| \sum_{n=1}^{N} x[n] \mathrm{e}^{-j2\pi f n T_S} \right|^2, \quad (1)$$

where $x[n]$ is the EEG signal of n samples and N is the total number of samples of the signal. Windows of 512 samples (2 s) were analysed with equation (1), the window was moved in steps of 64 samples (0.25 s). Then, the power of EEG rhythms are extracted from each window:

$$P_{\theta\, l} = \sum_{f=4}^{7} S(f); \;\; P_{\alpha\, l} = \sum_{f=8}^{13} S(f)\, ; \;\; P_{\beta\, l} = \sum_{f=14}^{30} S(f), \quad (2)$$

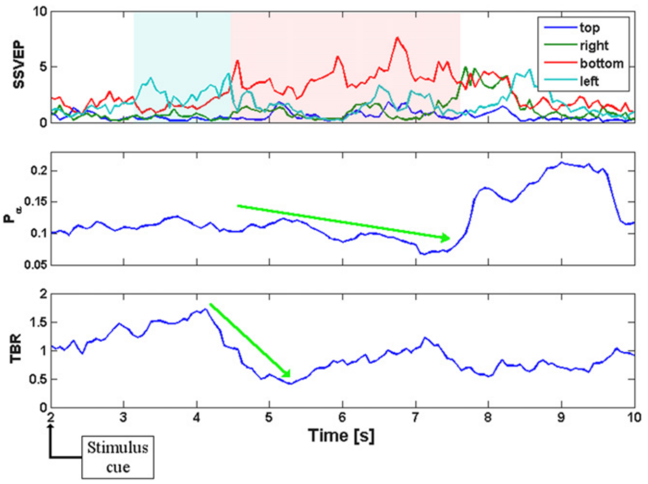

Figure 2. The SSVEP power elicited by each stimulus (up), the alpha rhythm power (P_α) at the middle and the theta/beta rate (TBR) at the bottom. In this trial, the volunteer was gazing at the bottom stimulus. SSVEP has been elicited in the light blue (incorrect) and red zones (correct). Green arrows indicate the transitory decrease of P_α and TBR.

where l is the number of window and, P_θ , P_α and P_β are the power of theta, alpha and beta rhythms, respectively. Then, theta/beta rate (TBR) is defined as:

$$\mathrm{TBR}_l = P_{\theta\, l}/P_{\beta\, l}. \tag{3}$$

According to other authors [19, 22], both TBR and P_α should decrease when the user is concentrated on a particular task. Therefore, as the user gazes at (and focuses on) a visual stimulus the TBR and P_α should decrease. In figure 2 the SSVEP power of the four stimuli is depicted, along with the TBR and P_α. In this trial, the volunteer should be concentrated on the bottom stimulus. Note that the SSVEP power corresponding to the bottom stimulus (red line in figure 2) is higher than other SSVEP powers between $t = 4.5$ s and $t = 7.5$ s, approximately (2.5 s after cue). Therefore, one can assume that in this period the volunteer focused on that stimulus. Then, in the same period, the P_α decreased slowly until $t = 7.5$ s, approximately. After that point, the P_α increased its value indicating a loss of concentration. On the other hand, TBR swiftly decreased at the beginning of the concentration-period and then increased slowly. Despite inter-trial and inter-volunteer variability, similar behaviour was observed along the database. In summary, when a volunteer gazed at a stimulus and truly focused on that stimulus, a decrease on the TBR and P_α was observed.

These measures were used to evaluate the concentration of the user on the stimulus, as is explained in the following section.

3.3. Hybrid BCI

In traditional SSVEP-based BCI, when an SSVEP is detected a command is sent to a device/application. In the scheme proposed here, when an SSVEP is detected, a validation process is triggered, and then the attention-level is evaluated on the same EEG channels where the SSVEP were detected. Figure 3 shows a scheme of the proposed hBCI.

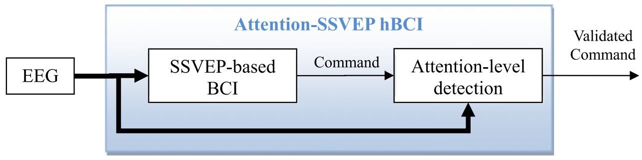

Figure 3. Schematic representation of the attention-SSVEP hBCI approach.

Hence, if the volunteer is concentrated, the command generated by the SSVEP-based BCI is validated and then, transferred to the device/application. In this way, the attention-SSVEP hBCI is more robust against false detections than traditional SSVEP-based BCI.

Based on the TBR and the P_α three different methods (and a contrast one) were proposed to validate the SSVEP detection, as follows:

Method A: no validation is performed, thus a traditional SSVEP-based BCI is implemented. This is used as the contrast method.

Method B: the SSVEP detection is validated when the next inequality is accomplished:

$$\sum_{l=H/2}^{H} \mathrm{TBR}_l < \sum_{l=1}^{H/2} \mathrm{TBR}_l, \tag{4}$$

where H is the time threshold (see section 3.1). In other words, the detection is validated when within the time window H, the value of TBR on the second half is minor than on the first half.

Method C: the TBR decreases when concentration increases, then the slope of the TBR is negative. A three-point derivative filter is applied and, the SSVEP detection is validated when inequality (5) is completed:

$$\mathrm{TBR}_l - \mathrm{TBR}_{(l-2)} < 0. \tag{5}$$

This inequality must be accomplished for at least 0.5 s to validate the SSVEP.

Method D: in this case, the slope of the P_α is evaluated by means of three-point derivative filter according to the following equation:

$$P_{\alpha R\, l} - P_{\alpha R (l-2)} < 0, \tag{6}$$

where $P_{\alpha R}$ is the relative alpha power, which is calculated at any time as:

$$P_{\alpha R} = \frac{P_\alpha}{\sum_{f=3}^{45} S(f)}. \tag{7}$$

Equation (6) must be fulfilled for a period of 0.5 s to validate the SSVEP.

As was mentioned the TBR and P_α should decrease when the user is concentrated on a particular task. Therefore,

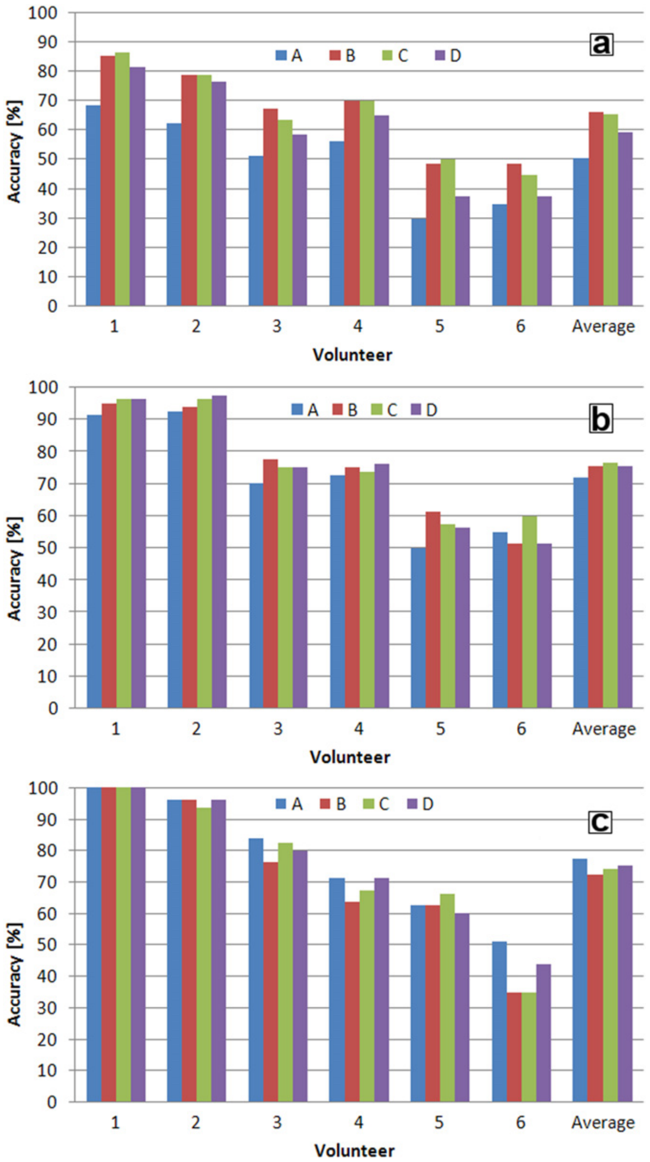

Figure 4. Detection accuracy for methods A, B, C and D evaluated for (a) $H = 1$ s , (b) $H = 1.5$ s and (c) $H = 2$ s.

we proposed different measurements in equations (4)–(7) to evaluate this descent. Additionally, these parameters do not need adjustments for each user, such as using thresholds.

4. Results

In order to evaluate the performance of the proposed methods, each trial could be classified as one of the next options: *correct* (the detected SSVEP corresponds to the stimulus indicated by the arrow on the screen), *incorrect* (the detected SSVEP is different from the stimulus indicated by the arrow on the screen) or *no-detection* (no SSVEP is detected). This last situation occurs when the volunteer does not concentrate enough on the light or the proposed method does not detect an SSVEP.

The rate between *correct* classified trials and the total number of trials is the detection accuracy. Figure 4 shows the

Figure 5. Average proportion on the detection of SSVEP. The relationship among correct, wrong (incorrect) and non-detected trials is depicted.

detection accuracy of the four proposed methods for every volunteer in the experiment. The detection accuracy was evaluated for different H values, namely $H = 1$ s, 1.5 s and 2 s. The SSVEP are easily detected (whether correct or incorrect) as the threshold H lowers. Therefore, the lower threshold ($H = 1$ s) is less robust against false detections than $H = 1.5$ s and 2 s. This can be observed in figure 5, where the proportion among correct, incorrect and non-detected trials is presented (average results among the volunteers are drawn). The improvements of the hBCI approach are easy to observe for lower H values. Detailed results for each volunteer are presented as supplementary data (stacks.iop.org/jne/12/056007/mmedia).

The average values of information transfer rate (ITR), sensitivity (SEN), specificity (SPE), positive predictive value (PPV) [26], false positive rate (FPR) [27], and detection time by trial are presented in table 1. Besides, other values related to the attention-level detection of the user are also shown in table 1. Specifically, they include: the average amount of validations per trial, i.e., the number of times the attention-level was evaluated until the detected SSVEP was validated; the number of trials where more than one validation step was needed; and finally, the average number of non-classified trials since the attention-level did not validate any detected SSVEP.

4.1. Statistical tests

Statistical tests were applied to evaluate the differences in the results. The number of cases is low and the normal distribution of the data cannot be assessed, consequently, two non-parametric statistical tests were used, namely the Friedman and the Wilcoxon test [28–30]. The Friedman test is a technique that can be applied to data classified by more than two criteria. Hence, the null hypothesis proposes that all the results are equivalent through the different methods. The alternative hypothesis is that at least two results are different.

For example, evaluating the accuracy results obtained with the four methods using $H = 1$ s, the Friedman test

Table 1. The average performance of the proposed methods.

					ITR (bits min^{-1})			Attention			
H (s)	Method	SEN (%)	SPE (%)	PPV (%)	Mean	Max	Elapsed time (s)	Validation per trial	Trial with two or more validations	Trial rejected	FPR
1	A	50.6	63.4	50.6	8.35	19.3	2.12 ± 1	—	—	—	0.37
	B	66.5	73.6	66.8	14.97	31.4	2.79 ± 1.1	2.5 ± 1.5	40	0.3	0.26
	C	65.6	73.2	66.0	14.86	32.9	2.8 ± 1.2	2.2 ± 1.4	41.5	0.5	0.27
	D	59.4	69.6	59.9	10.70	24.2	2.89 ± 1.4	3 ± 2.1	41	0.8	0.30
1.5	A	71.9	80.4	74.8	18.1	33.9	3.25 ± 1.1		—	—	0.20
	B	75.6	87	82.9	20.5	35.2	3.58 ± 1.2	2.9 ± 2.1	31	4	0.13
	C	76.5	86.2	82.2	20.3	36.5	3.6 ± 1.3	2.1 ± 1.3	32.2	2.5	0.14
	D	75.4	87	82.4	19.6	34.1	3.77 ± 1.3	2.9 ± 2	44.7	4	0.13
2	A	77.5	92.4	89.2	21.9	38.4	3.96 ± 1.2		—	—	0.08
	B	72.3	95.1	91.3	20.6	35.4	4.19 ± 1.2	3.4 ± 2.5	26.3	6.7	0.05
	C	74.2	94	90	20.2	34.3	4.19 ± 1.3	2.4 ± 1.8	30.2	4.2	0.06
	D	75.2	95	91.8	20.1	34.8	4.48 ± 1.2	2.9 ± 2	38.2	4.2	0.05

reports a p-value of 0.001 ($\chi 2 = 16.8$; $N = 6$; d.o.f. $= 3$). Hence, at least two of the four methods achieved results with statistically significant differences. Then, the Wilcoxon paired-test was applied to evaluate the differences between the four methods (three proposed methods and the contrast one). In this case, a minor p-value than 0.05 indicates statistically significant differences between both evaluated methods. For the same previous example, the Wilcoxon test reports a p-value of 0.027 between methods A and B, a p-value of 0.02 between methods A and C and finally, a p-value of 0.027 between methods A and D. On the other hand, the Friedman test applied over the accuracy results obtained with $H = 2$ s reports a p-value of 0.197 ($\chi 2 = 4.7$; $N = 6$; d.o.f. $= 3$). Thus, the null hypothesis cannot be rejected in favour of the alternative hypothesis, i.e. the four methods attained similar results.

The ITR values presented a similar behaviour when the statistical tests were applied, that is, statistically significant differences were reported for $H = 1$ s and 1.5 s whereas $H = 2$ s did not. Considering the PPV, the statistical tests always reported p-values lower than 0.05, which means that the improvements on the classification are statistically significant. The error rate was analysed as well, and the reduction of errors for methods B, C and D against method A was statistically verified. The SPE was analysed obtaining different results; sometimes the observed results presented statistical significance whereas others did not. Detailed results of the statistical tests for each volunteer are presented as supplementary data (stacks.iop.org/jne/12/056007/mmedia).

4.2. Idle state evaluation

This test was performed over the baseline EEG (see section 2). It is possible to consider this 60 s EEG segment as an idle state because the volunteer was gazing at the screen but definitely not concentrating on any stimuli. Theoretically, the BCI should not detect any SSVEP but the stimuli were still on the visual field of the user. Hence, any detection is a false positive.

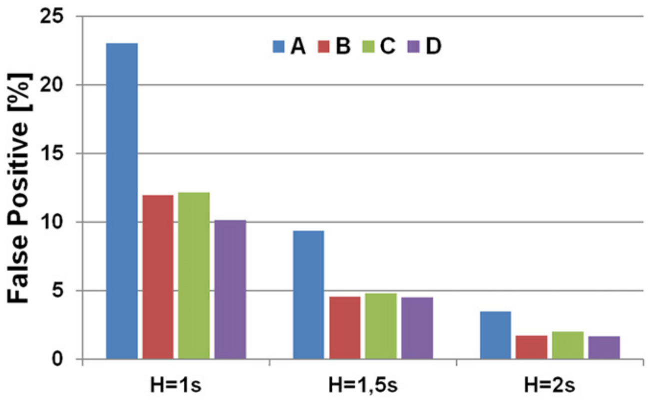

Figure 6. Average percentage of false postive evaluated as an asynchronous approach on the baseline EEG (idle state).

The processing signal method was applied as an asynchronous BCI paradigm every 0.25 s. Hence, discarding the initial 2 s window, 233 points were analysed, i.e., $(60\,\text{s} - 2\,\text{s})/0.25\,\text{s} + 1 = 233$. Figure 6 shows the average percentage of false positives for the three H thresholds. Detailed results on each volunteer are presented as supplementary data (stacks.iop.org/jne/12/056007/mmedia).

4.3. Evaluation on another database

The transitory response was extracted, analysed and evaluated over the same database, then in order to avoid some kind of over-fitting, the proposed methods were applied to another database. The database was previously acquired in a different research project [31]. In that work, the stimuli were presented at 13, 14, 15 and 16 Hz; the EEG was measured with two bipolar channels (O_1–P_3 and O_2–P_4) and, simultaneously with six monopolar channels at O_1, O_2, P_3, P_4, T_5 and T_6 referenced to F_Z and grounded at linked A_1–A_2. Each trial was

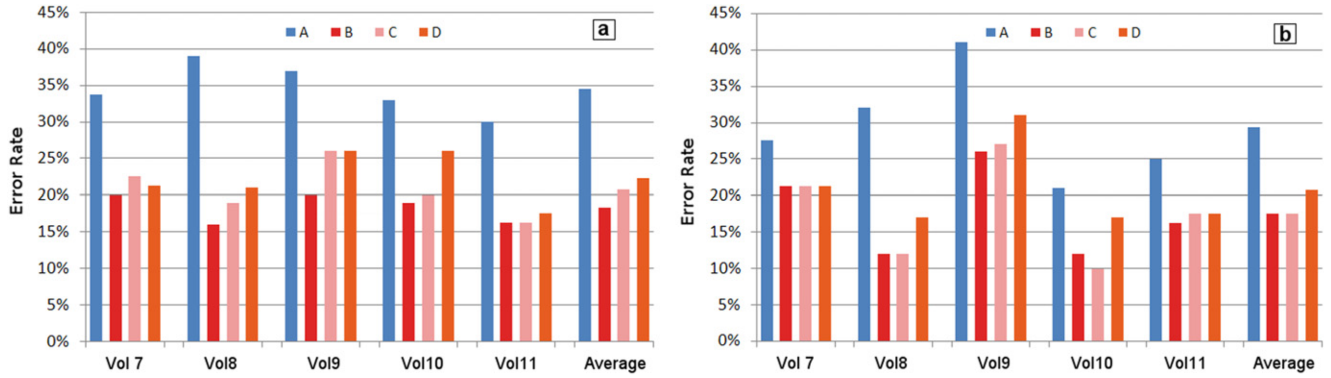

Figure 7. The error rate evaluated on the second database. The SVEEP were detected using (a) monopolar channels and (b) bipolar channels. In this case method A is the one implemented on [31].

similar to the current work but lasting 7 s. The stimulus to gaze at was indicated by an arrow on the screen at $t = 2$ s.

The same algorithm used in [31] was applied to detect the SSVEP and the proposed attention-level methods were used to validate those detections. Once again, the classification process began at $t = 2$ s because it represents an unfavourable situation.

The error rate obtained from the classification process of SSVEP on this second database was depicted in figure 7. In figure 7(a) the monopolar channels were used for SSVEP detection and in figure 7(b), the bipolar channels were used for detection. In both cases the attention-level was evaluated over the six monopolar channels as was previously described.

5. Discussion

This section was divided into three parts. The first one is devoted to discussing the performance of the proposed methods. Meanwhile, the second part analyses the behaviour of the P_α and TBR rate in the experiments. Finally, the hBCI approach is evaluated.

5.1. Evaluation of the results

Figure 4(a) presented the accuracy results evaluated for threshold $H = 1$ s. In this case, the threshold is low and thus, less robust against false positives. The accuracy on the classification was improved using the hBCI approach (with any method); moreover, it was statistically significant. On the average, method A (the contrast one) achieved 50% meanwhile, the hBCI achieved 66%, 65% and 59% for methods B, C and D, respectively. Therefore, the proposed hBCI improved the classification accuracy because erroneous detections were reduced (see figure 5). Hence, the wrong detections or false positives were diminished because when the user was not concentrating on the stimulus, the SSVEP was not validated (similarly to figure 2). This reduction on the error rate was verified by the statistical tests.

When threshold H was 1.5 s (figure 4(b)), the detection accuracy was improved for all methods from the results achieved for $H = 1$ s. Although the hBCI reached higher results, volunteer six presented some lower values. There is a possibility that volunteer six experienced some problems in maintaining his focus on the stimuli or perhaps the frequencies used in the experiment were personally unsuitable for him. Once again, the false positives were reduced but the no-detections were increased, as can be seen in figure 5.

Finally, for $H = 2$ s, different accuracies were found through the four methods for each volunteer. Although, method A looks superior, the average accuracy in figure 4(c) is similar for the four methods (between 72% and 77%). Moreover, those differences were not statistically significant, whereby it may be concluded that similar accuracies were achieved. On the other hand, the number of incorrect classified trials is lower for hBCI methods, as depicted in figure 5. This reduction was statistically significant.

The relationship among correct, wrong and non-detected trials (figure 5) is different for each method. As increasing H from 1 s up to 2 s, the correct detection rate is higher. However, method A obtains the highest wrong detection rate on any threshold H. The three proposed methods (B, C and D) increase the correct detection rate at the same time that wrong detections are diminished, sometimes at the cost of increasing the non-detected trials. The current hBCI has the capability of reducing the false positives (wrong detections), which are a problem in SSVEP-based BCI due to 'Midas touch effect'. Therefore, the proposed hBCI could diminish the false positives because the SSVEP is not validated if the user lacks concentration on the stimulus. Finally, the erroneously classified trials are reallocated as either correct or non-detected (figure 5). Depending on the application, it is generally preferable not to send a command (no detection) than to send the wrong one. For instance, if the BCI is used for commanding a wheelchair, a wrong command could cause an accident and/or injuries to the user.

The SEN measures the ability of the BCI to detect SSVEP, in table 1 this value is higher for the three proposed methods when $H = 1$ s and $H = 1.5$ s. The hBCI achieved similar SEN when $H = 2$ s, only volunteer six reported lower results for hBCI. On the other hand, the SPE refers to the ability of the BCI to correctly undetected SSVEP. Then, the SPE value is higher for methods B, C and D in all cases, that is, the hBCI is more robust against false positives. Generally, these SPE differences were statistically significant. The PPV represents the proportion of detections that are correct detections; the reported values show the superiority of the hBCI approach, which was statistically corroborated. The improvements on the SPE and PPV represent the advantages of the proposed hBCI. The FPR is as well presented in table 1, it constantly decreased from $H = 1$ s up to $H = 2$ s. Furthermore, FPR showed lower values for methods B, C and D than for method A. Hence, the three proposed methods are more robust against false detections.

The idle state was evaluated over the baseline EEG where any detection is a false positive. The three proposed methods reduced 50% the false positives of method A, as it was depicted in figure 6. Note that this evaluation was performed as an asynchronous paradigm and therefore, the feasibility of the proposed hBCI approach was confirmed.

Different approaches have been proposed to detect idle state. For example, Pan *et al* proposed a graphical user interface with pseudo-keys [4]. That system determines the control/idle state by comparison between the power of the target button and the pseudo-keys achieving a FPR of 4.17% and in asynchronous mode, 1 false positive by minute. In the current work, FPR of 5% was achieved (table 1) and 1.6% in asynchronous mode (baseline EEG). Ren *et al* determined the idle state with accuracy of 90% [3] and Wang *et al* achieved similar accuracy based on a strategy of excluding alpha wave interference [5]. In the current work, the idle state in the baseline was detected with average accuracy of 90% for $H = 1$ s, 95% for $H = 1.5$ s and 98% for $H = 2$ s (these values were calculated as 1-FPR on figure 6).

Note that method A is suitable for commanding devices since it has been successfully used to command a wheelchair [25] and a mobile robot [24]. Depending on each subject, method A achieved close to 40 bits min^{-1} in the current work (see the supplementary data stacks.iop.org/jne/12/056007/mmedia) or up to even 72.5 bits min^{-1} in [25]. The hBCI approaches overcame method A, and then it may improve the performance of the user in commanding mobile devices such as a wheelchair.

Conversely, the hBCI needed more time to detect an SSVEP. On average, the detection time rise is 0.77 s for $H = 1$ s and 0.52 s for other H values. Similarly, other researchers reported modulations of α-rhythm 400 ms after the onset of a spatial cue [20] and average latencies of around 500 ms [19]. Providing real-time feedback the hBCI approach may reduce the delay on detection time, however, it might be difficult to reduce it beyond of that average 400–500 ms limit. It depends on the application whether this delay might represent a problem or not. For example, generally, spellers focus on fast communication (spelling) but a wheelchair commanding focuses on safety navigation. Nonetheless, this delay affects the ITR by reducing it, although, the average ITR of the hBCI approach was higher than standard one. When $H = 2$ s the average ITR is a little bit higher for method A (21.9 bits min^{-1}) than for method B, C and D (20.6, 20.2, and 20.1, respectively); however these differences did not present statistical significance ($p = 0.073$). Thus, the increase on the detection accuracy is enough to counter the delay on the detection and, indeed increasing the ITR in some cases. In summary, the hBCI provides a higher rate of true positive and true negatives, which represents a more reliable BCI system. This is very important when transferring the BCI from the Lab to the home of the patient because each detected SSVEP is very likely to be the correct one.

A minimum of two or three validation steps per trial were required before the validation of an SSVEP. The processing signal method was performed in 0.25 s steps, thus, the validation process takes 0.5 s or 0.75 s on average. This is in accordance with the increase on the elapsed times shown in table 1 as well. Note that less than 50% of the trials (between 26.3 and 40 trials) needed two or more validations steps. In some cases, SSVEP were detected but the trial could not be classified because the detected SSVEP was not validated. This was expressed in the last column of table 1. In general, the average number of rejected trials was low; however, volunteer siox had some problems staying focused on the stimuli. Thus, his SSVEP were not validated in every trial and the number of rejected trials increased. Discarding volunteer six from this analysis, the average number of rejected trials did not exceed more than three or four per volunteer.

5.2. Analysis of the attention-level: the transitory response

Changes of the attention-level are reflected as changes in EEG signals. The EEG activity in the alpha, beta and theta rhythms [19–21] and θ/β ratio [22] is modulated by the attention-level. Then, when a person pays attention to any stimulus, some changes should appear in the EEG signal. We hypothesized that the attention-level can be measured along with the SSVEP on the same EEG channels. This hypothesis was verified in the current work. Moreover, it found a transitory response lasting a few seconds when the person starts to pay attention to any stimulus. In this transitory response, the alpha rhythm power and the θ/β ratio decreased. This behaviour of EEG signal is related to the attention change when the person gazes at a certain stimulus, instead of representing the whole attention-level of the volunteer (which is related with slow changes in brain rhythms).

SSVEP could be elicited in the same range of alpha, beta or theta rhythms, and then some interference may exist between attention-level and SSVEP detection. In this study SSVEP was elicited in the high-frequency range (>30 Hz) [23]. Nevertheless, note that SSVEP is just one specific frequency value and the attention-level is obtained from a wider frequency range. Moreover, some BCI approaches used SSVEP in the same range of spontaneous alpha rhythm despite this interference. Those BCI achieved high performances, indicating that interference is not necessarily a problem and it should be analysed in further research. In the current work, stimulation at high-frequency range was used because visual fatigue is reduced [23, 32]. Additionally, the hBCI was evaluated on medium-frequency range SSVEP (13, 14, 15 and 16 Hz) achieving high results.

The relative alpha power ($P_{\alpha R}$) was computed using the power of 3–45 Hz band as shown in equation (7). The SSVEP stimulation is within this band and therefore, it slightly modifies the $P_{\alpha R}$ value. In the current work, the behaviour of the $P_{\alpha R}$ is analysed instead of the $P_{\alpha R}$ value itself, that is, $P_{\alpha R}$ descends when the user focuses on the stimulus. Hence, this normalization did not affect the evaluation of $P_{\alpha R}$.

5.3. Evaluation of the hBCI approach

In SSVEP-based BCI, the stimuli are always found within the visual field of the user and consequently, false positives are reported (the 'Midas touch effect' [2]). For instance, in figure 2 the SSVEP corresponding to the left stimulus could be detected between $t = 3$ s and $t = 4.5$ s. Supposedly, the user was gazing at the bottom stimulus, even though an SSVEP of 1.5 s duration was elicited by the left stimulus (which is still within the visual field of the user). Other SSVEP detection methods such as canonical correlation analysis (CCA) [33] or minimum energy combination [34] should detect this SSVEP, however, it is still a false positive. For example, a recent improvement of a CCA method called CCA-RV (RV is reducing variation) [35] achieved very high performances in a spelling application, although it could still suffer from the Midas touch effect. Therefore, false detections must be reduced because wrong commands are produced. Moreover, the false detections are expected to appear more frequently in asynchronous BCI approaches and should be reduced as well. In the proposed hBCI the left-SSVEP was not validated because the criteria proposed in equations (4), (5) or (6) were not accomplished.

The proposed scheme, based on the detection of the attention-level, could be assembled with other SSVEP detection algorithms; thus more reliable systems could be obtained. Even those SSVEP detections algorithms that achieved perfect accuracies and/or highest rates, were generally evaluated over sessions of a few hours (in the best case). Nevertheless, using the system the entire day (as the case of people with disabilities), the effects of fatigue and user distraction becomes much more evident. Therefore, the proposed hBCI may mitigate them. Moreover, the proposed methods are simple and easy to calculate and consequently, they can be implemented in real-time applications.

Another advantage of the proposed approach is that it does not require the acquisition of other EEG channels beyond the ones used to detect the SSVEP. This differs from other hBCI approaches where more EEG channels are measured on different areas of the brain [7–10]. This results in a striking experiment because the attention information underlying in these EEG channels could be added to other SSVEP-based BCI. Moreover, the attention level of the user could quite possibly be easily detected using EEG measured from other parts of the head (e.g., frontal regions); however, this will require more hardware and more electrodes placed on the head of the user. Of course, this is more expensive and uncomfortable for the user. Therefore, this represents a prominent advantage of the proposed hBCI over other systems.

The proposed methods were evaluated on a different database. The EEG was acquired in a similar but different setup and the SSVEP were elicited at medium-frequency range (13, 14, 15 and 16 Hz). The obtained results verified our hypothesis, the proposed methods could be added to other BCI approaches and more important, an over-fitting hypothesis was avoided. In other words, the transitory response was detected in EEG signals from different people in a different BCI experiment. The error rate was reduced in all cases. When SSVEP were detected in O_1 and O_2, the error rate was decreased from 35% down to 20% on the average. Similarly, when bipolar channels were used, the error rate was diminished from 30% to 17%. In other words, an improvement of 15% is achieved, which is similar to the performance obtained on the high-frequency database when $H = 1$.

Particular comparisons with other hBCI approaches are not possible because there are no similar systems. Nevertheless, the current hBCI approach was implemented without any extra hardware and with simpler EEG signal processing methods, which represent advantages over other hBCIs.

The three proposed hBCI approaches obtained different performances on each volunteer, one approach sometimes resulted to be better than another; which made it difficult to choose the best method. A possible combination of the three approaches could improve the performances. However, developing the higher performance algorithm is not the purpose of this research. Instead, the aim was to show that extra information is encoded in the EEG along with the SSVEP, which indeed was verified in this work. It represents a novel approach and furthermore, this extra information has not been used in any current BCI approach.

6. Conclusions

This work proposes a different approach to SSVEP-based BCI, which relies on the estimation of the attention-level of the user. This information was used to validate the SSVEP detected by the BCI and thus, the performance of the hBCI was improved, mainly due to false positives rejected by the proposed algorithm.

Three measures were proposed to identify the attention-level based on the alpha power and TBR. A transitory response of EEG signal when the person gaze at (and pay attention to) any stimulus was found. Then, it is possible to determine whether the person is really focused on the stimulus being detected.

This approach shows some advantages. First, the attention-level variables were extracted from the same EEG channels used in the SSVEP detection. Hence, no extra electrodes or hardware were needed. Second, the proposed methods can be implemented in real-time applications because they are simple and easy to compute. Third, the current approach could be easily added to other SSVEP-based BCI algorithms, and consequently improve their performances.

Therefore, the performance of the hybrid approach is superior to the standard SSVEP-based approach. The proposed system is more reliable and robust against false detections because it reduces the error rate. This is very important on asynchronous BCI approaches. Thus, it could help in transferring the BCI systems to the home of the user.

Acknowledgments

The first, fourth and fifth authors are supported by CONICET: Consejo Nacional de Investigaciones Científicas y Técnicas (National Council for Scientific and Technological Research) from Argentina.

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