A Self-Paced and Calibration-Less SSVEP-Based Brain–Computer Interface Speller

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Abstract—**A brain–computer interface (BCI) is a communication system based on neural activity. Its goal is to provide a new output channel for the brain that requires voluntary control. We propose a new self-paced BCI speller based on the detection of steady-state visual evoked potential (SSVEP). The speller does not require any training from the user or from the signal processing part. The system is ready once the subject is prepared. The speller introduces a selection based on a decision tree and an undo command for correcting eventual errors. It was tested on eight healthy subjects who had no prior experience with the application. The average accuracy and information transfer rate are 92.25% and 37.62 bits per minute, which is translated in the speller with an average speed of 5.51 letters per minute.**

Index Terms—**Brain–computer interface (BCI), electroencephalogram (EEG), signal processing, speller, steady-state visual evoked potential (SSVEP).**

I. Introduction

A BRAIN–COMPUTER interface (BCI) is a system that allows people to communicate through direct neural activity measurements [1]–[3]. BCIs are the most useful for persons with severe disabilities, who are unable to communicate through any classical ways [4]–[6]. Although BCIs are mostly dedicated to disabled people, they could be efficiently used by healthy persons as a combination and complement with other interfaces [7], [8]. For these applications, BCIs may challenge other classical communication devices; they must be reliable, fast and provide efficient solutions.

Although current BCIs can leave the stage of laboratory demonstrators to real applications, many improvements are possible. Among them, the signal processing part can be improved by using advanced classification and machine learning techniques [9]–[12]. Second, the user can improve his performance by finding appropriate ways to adapt its behavior to the system or to some feedbacks [13]–[15]. For improving the performance, the system has to be trained in relation to the user or he has to spend some times with the application to use it efficiently. In both approaches, the performance increase is related to some calibration process or adaptation from the user.

The time spent with the application before its mastery can be an obstacle for extending the number of persons who would be willing to use (and buy) a BCI. New software must be quickly accessible to the potential user. The learning curve of a new application must be as fast as possible when the BCI has an entertainment purpose or challenge an existing communication control. For people who can only communicate with a BCI, a slow learning curve can be tolerated.

One other aspect to improve is the operating protocol. The user must have the total control of the system. In synchronous BCIs, the timing of operation is not determined by the user, but by the BCI. In asynchronous BCIs, the user can control the timing of communication. The terminology in the BCI field is not always consistent. Let us consider the "no control" state, which translates no intentional control. This state corresponds to when the user does not want to produce any command. This feature is relevant for BCIs that should be always available for disabled people. BCI systems that are continuously available to the user and support the "no control" state are called self-paced BCI. Asynchronous BCIs can be interpreted as BCIs with a "no control" state whereas synchronous BCIs do not support a "no control" state.

In this paper, we propose a new self-paced noninvasive BCI. The brain activity is recorded via EEG techniques. Such techniques have several advantages for extending the use of BCIs: the high time resolution, the portability, and relatively inexpensive equipments. The proposed BCI is based on steady-state visual evoked potentials (SSVEP). We therefore consider the response of the user attention to an oscillating visual stimulus. When a person looks at one particular oscillating light, his brain response can provide a way for creating a BCI. Usually, the stimuli that are used for inducing SSVEP responses are flickering lights at different frequencies. When an object flickers at a frequency f, then a response occurs in the visual cortex at the frequency of the stimulus and its higher harmonics [16]. Thus, different frequencies can involve different responses, which can be assigned to different commands. The SSVEP responses are described as reliable in the literature [17]–[19].

Visual evoked potentials based BCIs are described as more accessible than other BCI systems. They possess several advantages like a high information transfer rate (ITR) and little user training. However, SSVEP-based BCIs are not considered as independent BCIs as the generation of the visual evoked potentials depends on the gaze control via extraocular muscles and particular nerves. For this type of BCI, the only requirement is the possibility to control the eye movements. These BCIs are also often criticized for the annoying visual stimuli. We propose a new speller, which tries to fuse the visual stimuli and the application in one single and homogeneous way.

The paper is organized as follows. The speller is described in the second section. The third section deals with the experimental

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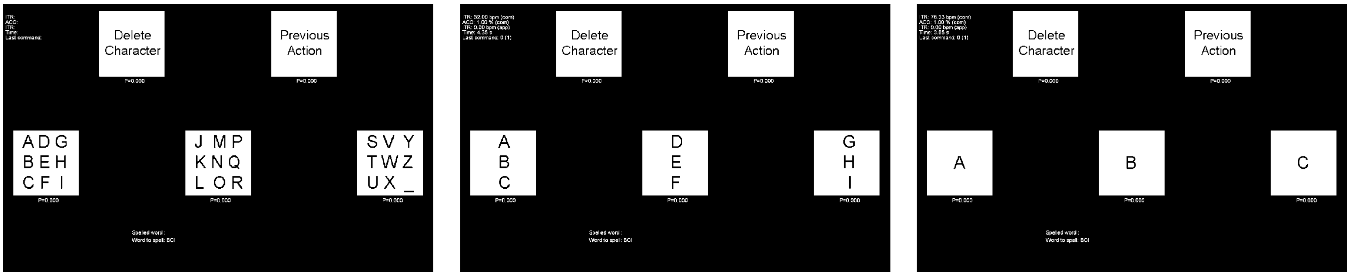

Fig. 1. Speller GUI. Example of the screen sequence for the selection of the letters "A," "B," or "C."

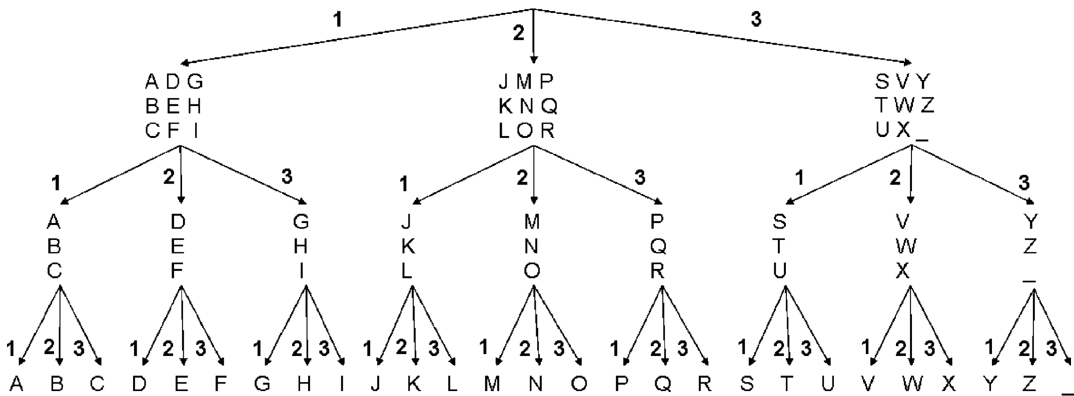

Fig. 2. Tree of the letters selection. (COM_1: $f = 6.666$ Hz, COM_2: $f = 7.500$ Hz, COM_3: $f = 8.571$ Hz).

protocol. The results are presented and discussed in the last two sections.

II. System Overview

The BCI presented thereafter is a speller that possesses several features: it is self-paced, it requires no training from the user, no calibration (no training from the signal processing part). The visual stimuli provoking event-related potentials are displayed on an LCD screen. They are fully integrated to the graphical user interface (GUI). This speller is therefore ready to work once the subject is prepared. The system is composed of two main parts: the GUI and the signal processing part, i.e., how the EEG signal is translated or not into a command in the speller. The speller allows writing 27 characters: the 26 Latin characters [A...Z] and "_" for separating the words. The SSVEP-based speller GUI is presented in Fig. 1.

A. Speller Commands

The selection of a letter is based on five main BCI commands, i.e., five flickering boxes.

- Three commands are dedicated to the navigation. We note COM_1, COM_2, and COM_3 these three commands. They correspond to the three boxes that contain all the possible letters in Fig. 1. For writing a letter, the user has to produce three commands. This number of command is fixed and independent of the letter. Fig. 2 displays the decision tree of selections and the succession of commands that are necessary for spelling one letter.
- One command is considered for canceling the previous one. Like for any current application, the "undo" command must be present for enabling easily a fast correction from the user. Indeed, an error can come from the user directly or indirectly. First, it can be due to a lack of attention, to the disrespect of what should be written. Second, the user wants to produce one command but the signal processing part provides the wrong command. In this case, the error is not voluntary and must be corrected easily. At any moment, the user is able to cancel the previous command with only one. This command aims at minimizing the cost of a mistake during spelling tasks. We note COM_4 the command for canceling the previous action or going up in the decision tree.
- One command is dedicated to the deletion of the last written character. At any moment, the user is able to suppress the last character of the text with only one command. We note COM_5 the delete action. It is possible to delete the letter that was just written with COM_4 but if the user does not correct it immediately, it is impossible to correct it without the COM_5 command.

After each command, an animation is displayed to signal to the user that a command has been produced. During this animation, every box stops to flicker. This short break of the flickering boxes lasts 1 s and it has two purposes. First, it gives to the user a visual feedback that a command was produced. The user cannot be aware of a misclassification if he is still watching one other flickering box. Second, the short break of the flickering boxes might improve the user comfort.

For COM_1, COM_2, and COM_3, the animation suggests that once one command is produced, the two other boxes of the menu disappear and the remaining box is split into three new boxes that move to the initial positions of the three previous choices. The goal of these animations is to smooth the gaze of the user.

The person can continuously focus on one particular letter and follow this letter while browsing in the decision tree, without any strong gaze shift to follow the new position of the boxes. For COM_4 and COM_5, the size of the box decreases for 0.5 s then it goes back to its initial size for 0.5 s. Although the impact of these animations is not evaluated in this study, they may contribute to the user comfort. It is important for the user to know in an efficient way when a command has been produced, wanted or not, while focusing on a flickering box.

B. Graphical Interface Features

Most of the SSVEP-BCI applications separate the visual stimuli from the application. Indeed, contrary to a P300-Speller [20], [21], where the user selects what he is looking at, BCIs based on SSVEP use the visual stimuli as a mean to navigate in one other interface or to control some devices [22], [23]. Some recent SSVEP-BCI studies have incorporated the visual stimuli in the application, like for video games [13], [24]. However, in these studies the use of flickering checker boxes can be an obstacle to fully integrate the stimuli in the GUI.

In the proposed speller, we merge the target and the visual stimuli like in the P300-Speller paradigm: "what you see is what you select." Besides, the letters in the flickering boxes do not flicker (the letters are always black). The user can focus on a letter, which does not flicker. Only the surrounding area of the center of attention is flickering. This feature might also decrease the annoying aspect of the flickering lights.

As depicted in Fig. 2, the inclusion of the letters in the visual stimuli is a mean to increase the size of the flickering boxes. As the GUI is embedded in the visual stimuli, there is no need to present an external layout of the speller like in [25]. This place is therefore saved to increase the size of the boxes, which is a natural way to improve the SSVEP response detection.

C. Frequency Selection

One issue to address is the optimal selection of the best frequencies for obtaining the best responses. This question has been largely discussed in the literature and it can depend on the subject [19], [26]. However, it is actually possible to get an SSVEP response with a large number of frequencies, from 1 to 100 Hz, with resonance peaks at 10, 20, 40, and 80 Hz [27]. Nevertheless, the best responses are obtained for stimulation frequencies between 5 and 20 Hz [28]. In addition, the device that renders the visual stimuli must be taken into account. As the speller is displayed on a common LCD screen, the refresh rate of this screen (60 Hz) is one parameter to take into account for choosing the frequencies of the flickering boxes. The choice of the frequency selection is first constrained by the vertical refresh rate. The frequencies to select are also determined by the number of commands and the frequency band to obtain SSVEP responses that can be detected easily. The five frequencies are selected in a narrow frequency band to avoid external effects, which could be related to other brain activity. If there are some disturbances in the signal, the effect will occur in every expected SSVEP response. The frequencies are chosen between 6.666 and 8.571 Hz. Table I presents the frequency to detect for each command and the structure of the oscillating signal. The structure denotes the signal pulse shape of one period of the stimulus signal. 1/0 denotes the colors black/white respectively that is rendered in one frame (one image displayed on the screen). As the refresh rate constraint is an obstacle for choosing five frequencies in a narrow frequency band, the signal structure for COM_4 and COM_5 is a composition of the structure of the other frequencies. These signal structures are assigned to the visual stimuli of COM_4 and COM_5; these two commands should not be often produced. Indeed, if one person does make no mistake in what s/he intends to spell, then COM_4 and COM_5 are not used.

TABLE I
FREQUENCY SET

Command	f [Hz]	Structure	# frames
COM_1	6.666	111110000	9
COM_2	7.500	11110000	8
COM_3	8.571	1111000	7
COM_4	7.059	11111000011110000	17
COM_5	8.000	111100001111000	15

D. Signal Processing

In this multiclass classification problem, we consider N_f classes where each class corresponds to an SSVEP response, i.e., a particular visual frequency. We consider a visual stimulation with a flicker-frequency of f Hz. We use the following analytical description for the signal $y_i(t)$ as the voltage between the electrode i and a reference electrode at time t

$$y_i(t) = \sum_{j=1}^{N_h} a_{i,j} \ \sin(2\pi j f t + \Phi_{i,j}) + B_{i,t} \tag{1}$$

where N_h is the number of considered harmonics.

The signal is decomposed into two parts: the response and the noise. The first part corresponds to the evoked SSVEP response signal, which is composed of a number of sinusoids with frequencies in relation to the stimulus frequency and a number of N_h harmonic frequencies. Each sinusoid is defined by its amplitude $a_{i,j}$ and its phase $\Phi_{i,j}$. The second part $B_{i,t}$ is dedicated to the noise. It can come from the environment and its effect on the subject, natural physical disturbance like other brain processes, breathing artifacts\cdots

The online detection of an SSVEP response on an EEG signal requires a time segment for the signal analysis. We consider a time segment of N_t samples of the signals, with a sampling frequency of F_s Hz

$$y_i = X a_i + B_i \tag{2}$$

where $y_i = [y_i(1), \ldots, y_i(N_t)]^T$ contains the EEG signal for the electrode i in one time segment. The SSVEP information matrix X is of size $N_t \times 2N_h$.

For N_y electrodes, the signal is defined as

$$Y = XA + B \tag{3}$$

where $Y = [y1, \ldots, y_{N_y}]$ contains the sampled EEG signals from all the electrodes. A contains all the amplitudes for all the expected sinusoids for all electrode signals.

The signals from the electrodes shall be combined for extracting discriminant features from the signal. We define a channel as a linear combination of the signals measured by different electrodes. These combinations can be in fact interpreted as spatial filters. A vector of channel data is denoted by s. Its purpose is to enhance the information contained in the EEG while reducing the nuisance signals. A channel s is defined by

$$s = \sum_{i=1}^{N_y} w_i y_i = Yw. \tag{4}$$

We note S the set of N_s channels by

$$S = YW \text{ with } S = [s_1, \ldots, s_{N_s}]. \tag{5}$$

Several channels can be created by using several sets of weights. The channel creation is an essential step toward the enhancement of the relevant signal [16], [29], [30]. In this work, we consider a generative approach based on the principal component analysis (PCA), which is described in [19]. It does not require any training or calibration step. The method assumes for each frequency that it is the right frequency to detect and removes the noise considering this hypothesis. It can generate a frequency power estimation of any frequency. Thus, channels are set in relation to hypotheses of the expected frequency to observe. First, the technique removes any potential discriminant components from all electrode signals, by projecting them onto the orthogonal complement of the formal model of the signal X

$$\tilde{Y} = Y - X(X^T X)^{-1} X^T Y \text{ and } \tilde{Y} \approx B. \tag{6}$$

PCA is applied on $\tilde{Y}$, and the eigenvectors will correspond to W. Its purpose is to have an optimal combination of the electrode signals, which cancel as much of the nuisance signals as possible. This method allows the combination of a fixed number of electrodes that minimize the nuisance signals. Once the channels are created, the power of the expected frequencies and their harmonics are calculated for each channel. For each frequency, the evaluation of the SSVEP response is defined by

$$R(f) = \frac{1}{N_s N_h} \sum_{k=1}^{k=N_s} \sum_{j=1}^{j=N_h} \left\| X(f)_j^T S_k \right\|^2 \tag{7}$$

where $X(f)$ is the SSVEP information matrix of the frequency f, and S_k is the kth channel. N_s is the number of channels equal to the number of electrodes and N_h is the number of considered harmonics. $N_h = 1$ is equivalent to using only the frequency of the visual stimulus. For the classification in the experiments, we set $N_h = 4$.

For the detection and classification of the SSVEP responses, we do not restrict the classification to the N_f frequencies to detect. Some other frequencies are also considered for improving the robustness of the decision [31]. Four other frequencies are added: 6.862, 7.279, 7.750, and 8.285 Hz. Each frequency is chosen between two frequencies to detect. Therefore, we consider nine different frequency powers for the classification, $N_f = 9$, (6.67, 7.50, 8.57, 7.06, and 8.00 Hz for the commands; 6.86, 7.28, 7.75, and 8.29 Hz for improving the reliability).

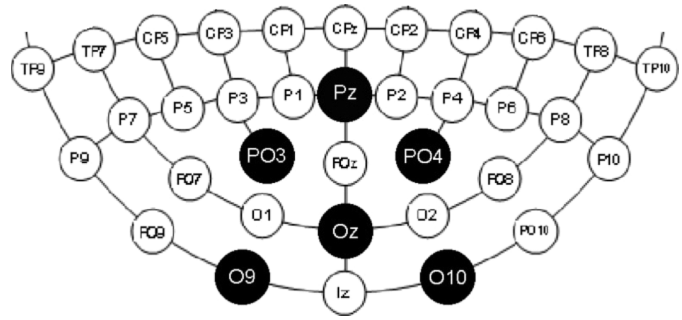

Fig. 3. Electrode placement at the back of the head.

The frequency power of each class is normalized into a probability by a softmax function, P_i is the probability to detect the frequency f_i, $0 < i \leq N_f$

$$P_i = \frac{e^{\alpha R_i}}{\sum_{j=1}^{j=N_f} e^{\alpha R_j}} \tag{8}$$

where α is set to 0.25. In the speller, the detection probability of the SSVEP response is given under each flickering box. This information is just useful for the experimenter.

The frequency corresponding to the highest probability is selected. The command corresponding to the frequency is produced if and only if the highest probability is superior to a fixed threshold (in the experiments it is 0.5) and if the frequency belongs to the frequency set of the commands. The threshold and α were set based on prior tests where the author was the system user

$$\text{COM}_i = \text{argmax}_i P_i \text{ and } P_i > 0.5 \text{ and } i < 6. \tag{9}$$

III. Experiments

A. Material

The conducted experiments are based on a noninvasive BCI that uses sensors with contact on the surface of the scalp via eight standard EEG electrodes. The location of the electrodes is the left and right earlobes for ground and reference, respectively. Six electrodes PO_3, PO_4, P_Z, O_{10}, O_9, O_Z are dedicated to the input features [32]. The location of these electrodes is presented in Fig. 3, which represents the back of the head. The impedances below 10 kΩ were achieved by using an abrasive electrode gel. The EEG data were acquired with an amplifier from g.tec, the sampling frequency was 128 Hz. During the EEG acquisition, an analog bandpass filter between 2 and 30 Hz, and a notch filter around 50 Hz (main frequency in Europe) were applied directly in the amplifier. For the software, an LCD screen with the resolution of 1680×1050 pixels and a refresh rate of 60 Hz was used. The luminance is about 180.0cd/m^2 with an estimated contrast of 280:1. Each flickering box is represented on 25.55cm^2, equivalent to a luminance of about 0.46 cd. The speller is developed in C++ uses DirectX 9 and its ID3DXSprite interface for displaying the flickering boxes and the animations. The subjects were sitting on a comfortable chair in front of the laptop.

B. Subjects

Eight healthy subjects participated in this study. They were all volunteers, unpaid, and belong to the same age group: the average age is 30 years, with a standard deviation of 3.66. Only one female subject was present (Subject 2). Subjects 3, 6, and 8 need vision correction and wore their glasses. Each subject has a previous SSVEP-BCI experience. They are not BCI-naive and are aware of the principle of an SSVEP-BCI system. However, they are all naive of the speller software and the visual stimuli frequencies.

C. Protocol

Before using the BCI, each subject was verbally informed about how the speller works. The experiment was composed of several sessions. In each session, the user had to write one of the following words: BCI, BRAIN, CERVEAU, SSVEP, BRAIN_COMPUTER_INTERFACE, the first name of the subject and one word chosen by the subject. There are therefore seven sessions for each subject. Between two sessions, a pause of 5 min is given to the subject to recover from eventual visual fatigue and to increase the relevance of the results over time. Each word has to be written completely and without any mistakes: COM_4 and COM_5 are present to correct eventual errors. In the best case, with no error, COM_4 and COM_5 should never be used. As the number of commands for writing one letter is fixed: three commands, the number of optimal commands is known for each session. The minimal number of trials per session is $3 * \#\mathrm{letters}$.

D. Parameters

Several parameters must be set for an SSVEP-based BCI. One of the most important parameters is the size of the segment length considered for producing a command, as it influences the speed of the system. The choice of its length is not easy. On one hand it is easier to detect an SSVEP response in a long time segment: it assures a high accuracy of the command detection. On the other hand, extending the time for the detection slows down the BCI. In [22], the control lag in an SSVEP-BCI was estimated to 1–5 s. In [13], Martinez *et al.* consider a sliding time window of 4 s. In [33], an average time of 3.4 s, 4.87 s, and 5.58 s are needed for the selection of a command for three subjects. In the presented speller, the time window considered for the signal analysis is 2 s, with an idle time of 2 s between two consecutive commands. It assures the possibility to produce a command relatively quickly.

IV. Results

Each subject could complete all the requested tasks without any problem. Table II presents for each subject the number of commands (# Com.), the total time (in minute) to complete every task, the accuracy of the BCI commands (in %), the average information transfer rate over the sessions [ITR, in bits per minute (bpm)], and the average number of letter per second.

TABLE II
RESULTS FOR EACH SUBJECT

Subject	#Com.	Time[min]	Acc.[%]	ITR[bpm]	[Letters/min]
1	237	13.97	84.00	28.19	4.01
2	200	9.32	93.52	41.59	6.11
3	207	11.10	94.64	38.17	5.31
4	196	11.21	94.88	35.22	5.17
5	197	8.45	97.45	47.18	7.34
6	203	10.14	92.12	36.71	5.62
7	219	10.19	90.20	40.16	5.59
8	192	10.83	91.22	33.69	4.89
MAX	237	13.97	97.45	47.18	7.34
MIN	192	8.45	84.00	28.19	4.01
MEAN	206.38	10.65	**92.25**	**37.62**	**5.51**
S.D.	14.89	1.63	4.05	5.67	0.96

The accuracy of the commands was calculated in relation to the best command to produce over time, to complete the requested tasks. The ITR, first introduced by Shannon and Weaver [34], is commonly used for measuring communication, control systems, and BCI [1]. The ITR is defined by

$$\Psi = \left(P\log_2 P+(1-P)\log_2\left(\frac{1-P}{N-1}\right)+\log_2 N\right) \quad (10)$$

$$\mathrm{ITR} = \frac{\#\mathrm{Com} * \Psi}{T} \quad (11)$$

where P is the probability to detect correctly a command, N is the number of commands ($N = 5$), and T (in minutes) is the time needed to produce $\#\mathrm{Com}$ commands. The best performance is obtained by Subject 5, with an average accuracy of 97.45% and an ITR of 47.18 bpm. The average accuracy and ITR over all subjects is 92.25% and 37.62 bpm, respectively. With a perfect accuracy, the maximum possible ITR is 69.66 bpm, $((\log(5)/\log(2)) * 60/2)$. Each subject is SSVEP-BCI literate and can correctly use the speller without any training. These results highlight the speller efficiency.

Table III presents the average time (in seconds) and the number of produced commands for each of the five commands when they correspond to a right classification, i.e., when the produced command is expected by the user. This time take into account 1 s of animation where the boxes stop to flicker and the time that the user needs to think about what is the next action to do for writing a word. Therefore, the time presented in Table III considers all the real time aspect of a BCI application. The minimum average time for producing a command is obtained with Subject 5 with 2.75 s. The average time over every subject is 3.44 s. The number of produced commands for COM_4 and COM_5 is not high, as these commands are only used for correcting mistakes. As expected, the average time needed to produce COM_4 and COM_5 is higher than for the other commands, which are based on a simple structure of the visual stimuli [35].

V. Discussion

BCI can work; it has been proven many times over this decade [3]. One of the current challenges to address is the use of BCIs beyond simple demonstration purposes: in a real environment and without the help of any expert for tuning the system. Such BCI shall be asynchronous/self-paced. The evaluation of such BCIs is one of the main directions for improving pragmatically BCIs. While BCIs are naturally expected to become faster and

TABLE III
AVERAGE TIME NEEDED FOR PRODUCING EACH COMMAND

Subject	COM_1		COM_2		COM_3		COM_4		COM_5		MEAN
	Time[s]	#Com	Time[s]	#Com	Time[s]	#Com	Time[s]	#Com	Time[s]	#Com	Time[s]
1	3.14	73	3.17	61	5.43	57	4.83	4	3.63	5	4.04
2	2.65	68	2.90	55	2.80	49	3.75	1	3.72	10	3.16
3	3.23	70	3.32	64	3.18	55	4.12	1	3.66	3	3.50
4	3.43	61	3.41	61	3.68	51	-	-	3.84	9	3.59
5	2.61	68	2.48	58	2.78	55	-	-	3.13	5	**2.75**
6	3.02	66	2.96	56	3.03	54	4.63	2	3.57	9	3.44
7	2.77	72	3.17	52	2.87	55	4.56	2	3.26	14	3.33
8	3.37	64	3.24	49	3.50	50	3.63	2	4.76	12	3.70
MIN	2.61	61.00	2.48	49.00	2.78	49.00	3.63	1.00	3.13	3.00	2.75
MAX	3.43	73.00	3.41	64.00	5.43	57.00	4.83	4.00	4.76	14.00	4.04
MEAN	3.03	67.75	3.08	57.00	3.41	53.25	4.25	2.00	3.70	8.38	**3.44**
S.D.	0.32	4.03	0.30	5.01	0.88	2.87	0.50	1.10	0.49	3.78	0.38

more reliable, they still must be user friendly, and propose an operating mode that allows them to be used outside a laboratory. For a BCI user, like a patient, his primary goal is not to send bits to a computer. The patient wants to communicate with the real world thanks to external devices or software; the inner notion ofBCI limits the communication scope to the computer stage. The real BCI meaning is indeed brain–real world interface, which can be translated for instance by the speller speed.

The BCI constraints the user interfaces with a restricted number of possible commands. For one application, like a speller, several solutions are possible and they depend on the particular brain response to detect. BCI spellers are mostly based on the P300 paradigm that is not self-paced. A P300 speller GUI consists in displaying a $N \times N$ matrix composed by letters, usually $N = 6$. Contrary to the P300 paradigm, where each cell of the matrix can correspond directly to a letter, the low number of commands in an SSVEP-BCI or in an imagery based BCI involves a particular strategy for creating the graphical user interface. For motor imagery based BCI, Blankertz *et al.* proposed a speller called hex-o-spell that uses only two mental states [36]. The typing speed of the hex-o-spell is between 2.3 and 5 letters/min for one subject and between 4.6 and 7.6 letters/min for a second subject. For the proposed SSVEP speller, the average speed over eight subjects is 5.51 letters/min, with Subject 5 going up to 7.34 letters/min.

The BCI and the application that must be controlled are often considered as two separate parts. When it is possible to separate the visual stimuli from the application, the choice of LEDs for the visual stimuli may be more judicious as the frequencies can be chosen and LEDs can provide a higher intensity of the lights [35]. As BCIs must take into account the ergonomic aspect of the application, some commands shall be present like "undo" or "delete character," as described in this study. These commands are not a confession of failure: a perfect accuracy over time is hard to achieve. Besides, the user may produce some involuntary mistakes. The GUI with LCD screens has a cost: the frequency choice is limited and the intensity of the lights can be inferior to a device based on LEDs. However, new LCD monitors with a refresh rate of 120 Hz can provide a wider choice of frequencies.

The number of basic BCI commands in an SSVEP-BCI is a critical choice. With a high number of commands, it is possible to directly assign one BCI command to one main action of the application [33], [37]. With less commands, a strategy has to be found for combining the basic commands. While the use of few commands can be a drawback, it is interesting to mention that it is easier to select several times the same command in a row. As the sequence of commands corresponds to the same visual stimulus, there is no lag due to gaze shifting. For instance, the user has to focus on the same target for three commands for writing the letter "A." This observation could be taken into account for changing the order of the letters in the decision tree: the letters with a high probability, like "E," could be written by using three times the same command.

The proposed speller does not consider parameters based on the user. The speller requires no training from the user, no particular calibration for setting thresholds. Only two variables are fixed for the classification: the threshold and the softmax parameters. While they can be set in relation to the user, the parameters were chosen before the experiments and still provided good results for each subject. The choice of personalized parameters is a natural way for improving the performance. However, such procedure can be a drawback for healthy people. The gain given by the personalization of the BCI shall be weighed with the required time needed to improve the performance. The speller without calibration is one step toward plug'n'play BCIs as once the user is "plugged," the speller is ready to work. Although it is possible to use directly and efficiently a BCI from the software point of view, the time for preparing a user is still important and depends on the user, the hardware devices, the type of electrode and the gel.

VI. CONCLUSION

A new self-paced SSVEP-based speller has been presented. It does not require a calibration procedure. It allows writing letters at an average speed of 5.51 letters per minute (with a choice between 27 characters). The obtained performance is promising for its use with disabled people. The proposed speller can be easily transformed for other applications like for robotic or domotic controls. Further works will deal with improving the GUI for extending the possible number of letters and to include knowledge about the vocabulary for creating an optimized decision tree in relation to the language of the user.

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