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2011 J. Neural Eng. 8 036020

(http://iopscience.iop.org/1741-2552/8/3/036020)

IOP Publishing | Journal of Neural Engineering

J. Neural Eng. **8** (2011) 036020 (11pp) doi:10.1088/1741-2560/8/3/036020

SSVEP-based Bremen–BCI interface—boosting information transfer rates

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Received 17 November 2010, in final form 3 February 2011
Published 10 May 2011
Online at stacks.iop.org/JNE/8/036020

Abstract

In recent years, there has been increased interest in using steady-state visual evoked potentials (SSVEP) in brain–computer interface (BCI) systems; the SSVEP approach currently provides the fastest and most reliable communication paradigm for the implementation of a non-invasive BCI. This paper presents recent developments in the signal processing of the SSVEP-based Bremen BCI system, which allowed one of the subjects in an online experiment to reach a peak information transfer rate (ITR) of 124 bit min^{-1}. It is worth mentioning that this ITR value is higher than all values previously published in the literature for any kind of BCI paradigm.

S Online supplementary data available from stacks.iop.org/JNE/8/036020/mmedia

(Some figures in this article are in colour only in the electronic version)

1. Introduction

Brain-computer interface (BCI) systems allow people to interact with the environment through an alternative communication channel that is entirely independent from the traditional motor output pathways of the nervous system [1–3]. These devices use brain activity as the input signal and may be the only possible means of communication for people with severe motor disabilities [4, 5]. Recent studies have indicated increased interest in BCI systems that are based on various sensor modalities [6]. In non-invasive BCIs, electroencephalography (EEG) is commonly used because of its good time resolution, ease of EEG data acquisition and lower system cost compared to other brain activity monitoring modalities [7, 8].

Nowadays, the SSVEP approach provides the fastest and the most reliable communication paradigm for the implementation of a non-invasive BCI system [9–14]. The performance of the BCI can be assessed by the information transfer rate (ITR), as introduced in [15] and reported in the majority of BCI studies. This measure depends on three factors: speed, accuracy and number of targets, which can vary from 2 [16] to up to 48 [17]. In a six target SSVEP-based BCI, an average accuracy of 95.3% and ITR of 58 ± 9.6 bit min^{-1} for 12 healthy participants were reported in [18]. Using a different type of SSVEP stimulation, the so-called code-based modulation technique, where pseudorandom sequences are displayed to the user (instead of frequency-based modulation with boxes flickering with different constant frequencies, which is used here), the same research group reported ITR values of 92.8 ± 14.1 bit min^{-1} [19]. However, high ITRs are not the only essential characteristics for a BCI. In order to make BCIs more practical for a wide group of users with communication deficits in real-world settings, BCI accessibility, flexibility and usability must be substantially improved. Our recent study [20] presents a new hardware development, already successfully validated for use in SSVEP-based BCIs: EEG electrodes that require tap water instead of abrasive electrolytic electrode gel. These electrodes make both the daily setup and the clean-up much faster and easier, and also more comfortable and dignified. By using these electrodes, the clean-up procedure (washing the remaining electrode gel out of the hair) is no longer necessary and can simply be omitted.

Another very important topic in the BCI research field is the so-called BCI illiteracy (also called BCI deficiency). Ideally, an interface should work for any user. However, across the major noninvasive BCI approaches, numerous labs have reported that very roughly 20% of subjects cannot achieve control of the interface. These subjects, unable to use the BCI system, have usually been called 'BCI illiterates', e.g. [21]. Although extensive efforts have been made to overcome this problem through various mechanisms, there is still no 'universal BCI' that suits all users.

The continuous improvement of signal processing algorithms carried out in our group during the past few years has allowed us to reduce the number of BCI illiterates for SSVEP-based BCI as follows:

- CeBIT 2008 (March 2008) 26 subjects out of 106 participants (24.53%) are BCI illiterates [22].
- RehaCare 2008 (October 2008) 5 subjects out of 37 participants (13.51%) are BCI illiterates [23].
- HannoverMesse 2010 (April 2010) 2 subjects out of 86 participants (2.33%) are BCI illiterates [24].

These achievements made the difference between an ineffective system and a working SSVEP BCI for some users in our lab who were previously counted as 'illiterates'. Building on these improvements, our main effort now is to increase the information transfer rate of BCIs. High ITRs are essential for a BCI in order to become a practical device for communication and control, such as a speller application, and are important in order to control an external device, such as a wheelchair or a neuroprosthesis.

This paper presents the recent developments in the SSVEP-based Bremen BCI system, which have led to boosting the ITR to more than 100 bit min^{-1}. Two main aspects can be distinguished: (a) various updates and improvements in the signal processing methods, and (b) the development of the user friendly and intuitive graphical user interface (GUI) based on the online feedback to the user.

In comparison to our previous work [25], which was used as groundwork for the novel signal processing algorithm presented here, the following three major changes in the SSVEP signal processing should be noted in particular:

- In order to detect the presence of a frequency in the spatially filtered signals, the power in the stimulating frequency and their harmonics were used instead of the signal-to noise ratio used in the original method.
- We introduced a completely new method of SSVEP detection based on the utilization of four additional frequencies to detect, which are selected between target frequencies (and do not correspond to any of the command classes to detect).
- We introduced an adaptive mechanism of time segment length adaptation for SSVEP command classification.

This paper is organized as follows. The second section discusses the details of the proposed improvements of the SSVEP-based Bremen BCI system. The results we achieved are presented in the third section, followed by the discussion and conclusion in the final two sections.

2. Methods and materials

2.1. Bremen BCI spelling application

The GUI of the Bremen BCI speller is presented in figure 1. It consists of a virtual keyboard with 32 characters (letters and special symbols) and five white stimulation boxes. These boxes are located at the outer edges and the upper left corner of the screen, and they flicker with different frequencies. As the quality of the SSVEP response depends on the stability of the frequencies, the five stimulation frequencies that are used in this experiment were selected on the basis of the refresh rate of the LCD screen (120 Hz) that produces the stimuli: 6.67 Hz ('select'), 7.50 Hz ('left'), 8.57 Hz ('right'), 10.00 Hz ('up') and 12.00 Hz ('down'). In previous studies [26, 27], the selection of these frequencies was discussed thoroughly. This setup, as opposed to having an LCD for the GUI and a separate LED board for the visual stimuli, is much more convenient for users as they do not have to shift their gaze too much. Further details about the software design and implementation of this GUI application can be found in [3, 23, 28].

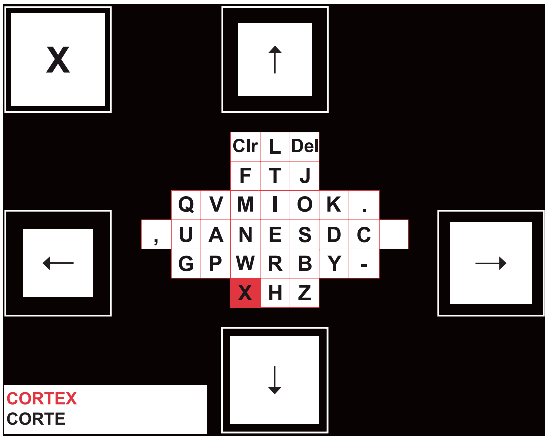

Figure 1. GUI of the SSVEP-based Bremen BCI during an online experiment, when a subject was spelling the word 'CORTEX' and the letter 'X' was about to be selected. A cursor can be navigated left, right, up and down until the desired letter is reached. With the 'select' command, a letter is selected and displayed at the bottom of the screen. At the beginning of the experiment and after every selection, the cursor automatically moves back to the initial letter 'E'.

At the beginning of each trial, the cursor is located in the middle of the virtual keyboard, over the letter 'E', and all flickering boxes are presented in their default size of 150 × 150 pixels. During the spelling task, by focusing the user's attention on one of the four flickering boxes, the cursor is navigated by the commands 'left', 'right', 'up' and 'down' until the desired letter is reached. With the 'select' command, a character is selected and displayed at the bottom of the screen, as shown in figure 1. Audio feedback, the name of the classified command or the name of the letter in the case of 'select', follows after every recognized command. After each selection, the cursor automatically moves back to the initial letter 'E'. The number of commands required for letter selection varies from letter to letter—from the minimum of one (selection of the letter 'E' in the middle of the speller layout with just one 'select' command) to a maximum of five commands (e.g. the selection of the letter 'G', which requires four movement commands and the following selection). The letters are arranged according to the frequency of occurrence in the English language, and the additional special characters are located at the border. This letter arrangement helps to increase the speed of text input and was selected and thoroughly compared during previous work of our group [3]. A minimum of nine commands are needed in order to spell the word 'BCI.' The letter 'B' can therefore be reached in two different ways: (1) 'down', 'right' or (2) 'right', 'down'. Both paths are judged as correct command sequences. In case one wrong command is detected, the user should correct this error first (e.g. an additional command 'right' after the wrong command 'left'). Therefore, the correction step is counted as a correct command classification in this case.

During the experiment, the sizes of flickering boxes vary in relation to the SSVEP amplitude. The white frames around each stimulus box (of equal fixed size of 250 × 250 pixels) represent the maximum size that a stimulus can reach without classification. This helps the user to know whether a command is executed. This novel continuous real-time visual feedback about the power of SSVEP signals additionally improves the time behaviour of the BCI system. In general, the amplitude of the SSVEP response depends on the size of the visual stimuli. Larger stimuli produce better responses. These changes represent the positive feedback in the overall BCI system.

Navigation cannot move beyond the layout boundaries. For example, it is not possible to go from the letter 'G' to the letter 'Q' by choosing the 'down' command. All of these modifications improve the comfort and easy use of the SSVEP-based Bremen BCI and also increase the overall reliability of the system. The box at the bottom of the screen contains—for the copy spelling mode—the word to spell and the actual spelled text. Figure 1 shows a screenshot taken during the online spelling task, when a subject spelled the word 'CORTEX'. After the subject had successfully spelled the letters 'CORTE', the cursor was navigated over the last character, the letter 'X'.

In contrast to our previous system implementation, the feature of deactivation of the stimuli when the current cursor position is on the edge of the speller layout was disabled. When the number of stimuli varies during the experiment, the true number of targets should be used for the calculation of the ITR. Since this feature results in significant complications in the ITR calculation and leads only to very minor improvements in the ITR, the number of stimuli was kept unchanged in order to test the ITR in the conventional way. Another change concerns the visualization of the navigation commands on the four boxes at the outer edges of the LCD screen: most users preferred to have the navigating arrows on the boxes without changes instead of displaying the next target letters for each navigation command on the corresponding flickering box. The reason for this change was that this kind of feedback was very confusing for naive subjects and resulted in many wrong selections when the cursor was located just one step away from the desired letter.

2.2. SSVEP signal processing

The SSVEP signal detection and classification methods are the core of this project. The minimum energy combination (MEC) method [25] was used to create a spatial filter that magnifies the SSVEP response and cancels nuisance signals and noise. The BCI automatically determined the best spatial filter for each subject at each stimulation frequency. SSVEP detection is based on power estimation after spatial filtering and a statistical probability method that enhances signal separability. Moreover, an adaptive mechanism is used to select the appropriate window length depending on the subject's online performance. This classification algorithm was implemented in MS Visual C++ building an asynchronous, real-time BCI system. The complete signal processing approach used for online classification of SSVEP responses is summarized in the following.

2.2.1. SSVEP response and modeling.

An SSVEP BCI reflects the user's attention to an oscillating visual stimulus. The commonly used stimuli are light sources flickering at different frequencies. They elicit responses mainly in the visual cortex of the brain, corresponding to SSVEPs at the same frequencies and their higher harmonics. The amplitude and the phase that define an SSVEP response depend on the frequency, intensity and structure of the repetitive visual pattern [29]. It is possible to obtain an SSVEP response at a large range of frequencies, from 1 to 90 Hz [30]; however, the strongest responses are typically obtained for lower stimulation frequencies around 15 Hz [31]. Gao *et al* [17] have observed that two flickering targets with a frequency difference as low as 0.2 Hz can be successfully distinguished in the SSVEP response.

To model an SSVEP response, a visual stimulation with a flicker frequency of f Hz is considered. The voltage between the ith electrode and a reference electrode at time t, $y_i(t)$, can then be described as a function of the stimulus frequency, f, and its harmonics, subject to a phase-shift, and a noise and nuisance signal, $E_{i,t}$,

$$y_i(t) = \sum_{k=1}^{N_h}(a_{i,k}\,\sin 2\pi kft + b_{i,k}\cos 2\pi kft) + E_{i,t}, \qquad (1)$$

where N_h is the number of considered harmonics. The model is linear and the signal is composed of two parts. The first part corresponds to the visually evoked response signal, which is composed of a number of sine and cosine functions at the harmonic frequencies kf with specific amplitudes, $a_{i,k}$ and $b_{i,k}$. The second part of the model, $E_{i,t}$, represents all of the information that cannot be attributed to the SSVEP response, such as environmental noise and its effect on the subject, and natural physical disturbances, like other background brain processes and various kinds of artefacts.

For a time segment of length T_s, acquired with a sampling frequency of F_s Hz, which contains N_t samples of the ith signal, the model can be expressed in vector form as

$$y_i = Xg_i + E_i, \qquad (2)$$

where $y_i = [y_i(1), \ldots, y_i(N_t)]^T$ contains the EEG signal for the electrode i in the time segment used for the signal analysis. The SSVEP information matrix X is of size $N_t \times 2N_h$ and contains the sine and cosine components associated with the N_h harmonics, while the vector g_i of size $2N_h \times 1$ contains the corresponding amplitudes $a_{i,k}$ and $b_{i,k}$. Equation (2) can be generalized for N_y electrodes

$$Y = XG + E, \tag{3}$$

where $Y = [y_1, \ldots, y_{N_y}]$ contains the sampled EEG signals from all of the electrodes. The matrix G of size $2N_h \times N_y$ contains all of the amplitudes for all of the expected sinusoids for all electrode signals.

2.2.2. Minimum energy combination. To extract discriminant features, the signals from the i electrodes need to be combined. This can be achieved by defining a channel vector s of length N_t, which is a linear combination of the electrode signals, y_i,

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

where w is a vector of weights $[w_1, \ldots, w_{N_y}]$ associated with the individual electrode signals. The aim of channel s is to enhance the information contained in the EEG while reducing the nuisance signals. Several channels can be created by using different sets of weights, depending on the nature of the SSVEP signal and the noise. Equation (4) can be generalized for N_s channels as

$$S = YW, \tag{5}$$

with the set of channels $S = [s_1, \ldots, s_{N_s}]$ and the corresponding weight matrix $W = [w_1, \ldots, w_{Ns}]$.

As a first step, an orthogonal projection is used to remove any potential SSVEP activity from the recorded signal,

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

The remaining signal $\tilde{Y}$ contains approximately only noise, artefacts and background brain activity.

In the next step, the weight vector $\hat{w}$ is found, which minimizes the energy of the signal $\tilde{Y}$, by optimizing

$$\min_{\hat{w}} \|\tilde{Y}\hat{w}\|^2 = \min_{\hat{w}} \hat{w}^T \tilde{Y}^T \tilde{Y} \hat{w}, \tag{7}$$

which will minimize the component of the noise and nuisance signals in the corresponding channel signal (equation (4)). As shown in [25], the lower bound of the quadratic form on the right-hand side of equation (7) is given by the minimal eigenvalue λ_1 of the matrix $\tilde{Y}^T\tilde{Y}$. The solution is therefore the corresponding eigenvector, v_1, which gives the weight vector for one channel. Additional uncorrelated channels can be added by choosing the next smallest eigenvalue (and corresponding eigenvector). The weight matrix can therefore be chosen based on the eigenvalues in ascending order $(\lambda_1, \lambda_2, \ldots)$ and the corresponding eigenvectors $(v_1, v_2, \ldots)$,

$$W = \left[\frac{v_1}{\sqrt{\lambda_1}} \cdots \frac{v_{N_s}}{\sqrt{\lambda_{N_s}}} \right]. \tag{8}$$

The total number of channels used, N_s, is selected by finding the smallest value for N_s that satisfies

$$\frac{\sum_{i=1}^{N_s} \lambda_i}{\sum_{j=1}^{N_y} \lambda_j} > 0.1. \tag{9}$$

This can be interpreted as selecting the number of channels in such a way as to discard as close to 90% of the nuisance signal energy as possible [25].

2.2.3. SSVEP detection. To detect the presence of a frequency in the spatially filtered signals, the power in that frequency and a number of harmonics N_h can be estimated by

$$\hat{P} = \frac{1}{N_s N_h} \sum_{l=1}^{N_s} \sum_{k=1}^{N_h} \|X_k^T s_l\|^2. \tag{10}$$

In the actual system implementation, $N_h = 2$ to avoid overlapping between the frequencies is used. If more harmonics should be taken into consideration, the used frequency set should be changed. So, e.g., the stimulating frequency of 10 Hz cannot be chosen if the frequency 6.67 Hz is already in the set, because the second harmonic of 10 Hz is equal to the third harmonic of 6.67 Hz. For more details regarding a thorough discussion of frequency selection to be generated on the LCD screens, please refer to [26].

In a BCI application, only the frequencies with which the user is stimulated should produce a control signal. To improve the robustness of the classification, not only are the stimulation frequencies considered but also a number of additional frequencies, as originally proposed in [32]. We consider four additional frequencies to improve the reliability of the outputs: 7.08, 8.03, 9.28 and 11.00 Hz. These frequencies are selected as means between two target frequencies. For instance, 7.08 Hz is the mean value of 6.66 and 7.50. The purpose of these frequencies is to improve the quality of the detection of the frequencies of interest, as described below.

The SSVEP power estimations for all frequencies N_f, in the considered case $N_f = 9$, are normalized into probabilities,

$$p_i = \frac{\hat{P}_i}{\sum_{j=1}^{j=N_f} \hat{P}_j} \qquad \text{with} \qquad \sum_{i=1}^{i=N_f} p_i = 1, \tag{11}$$

where $\hat{P}_i$ is the ith signal power estimation, $1 \leqslant i \leqslant N_f$.

A high probability will become more difficult to achieve when N_f is large (i.e. adding other frequencies amplifies this effect). Also, we use a Softmax function to enhance the gap between the values,

$$p_i' = \frac{e^{\alpha p_i}}{\sum_{j=1}^{j=N_f} e^{\alpha p_j}} \qquad \text{with} \qquad \sum_{i=1}^{i=N_f} p_i' = 1, \tag{12}$$

where α is set to 0.25 (based on our prior practical investigations and on the number of frequencies used N_f). The output values of the Softmax function are between 0 and 1; their sum is equal to 1. This is a generalization of the logistic function to multiple variables. Although this function does not change the distribution of the frequency powers, it improves the relevance of the command detection. Higher α values reduce the time needed for the single command classification. However, values higher than 0.3 would produce many false positives and should be avoided.

2.2.4. Signal classification. The classifier output O is determined as the number of the ith frequency if (1) this ith frequency has the highest probability p_i', (2) p_i' exceeds the pre-defined threshold β_i and (3) the detected frequency belongs to one of the stimulating frequencies,

$$O = \begin{cases} \operatorname{argmax}_i(p_i'), \\ p_i' \geqslant \beta_i, \\ i \leqslant 5 \end{cases}, \tag{13}$$

where $1 \leqslant i \leqslant N_f$ and β_i vary between 0.5 and 0.3 ($\beta_1 = 0.45$, $\beta_2 = 0.4$, $\beta_3 = 0.35$, $\beta_4 = 0.3$, $\beta_5 = 0.5$). In general, visual stimulation with lower frequencies produces higher SSVEP responses; this is the reason for selecting different β_i in descending order according to the stimulation frequency. This choice of β_i is based on our prior practical investigations (work with offline data collected from field studies with a large number of subjects in order to achieve faster SSVEP classification, e.g. [33]), the frequency to be classified, and the number of used frequencies N_f.

If O is classified as an undesired frequency ($i > 5$), then this classification will be rejected as the detected frequency does not belong to the expected frequency set. To improve the overall reliability of the system, the commands corresponding to the stimulating frequencies are produced only if their probability is higher than the fixed thresholds β_i.

The main advantage of the methodology outlined above is the fact that the pre-defined thresholds β_i represent the relative probabilistic values and not the absolute threshold values, as in the original method [25, 28], and as such they are independent of changes in the segment length T_s of the acquired EEG signal used for classification.

The classification has to take the moment into account when the user does not focus on any stimuli. Therefore, the classifier output detects a resting state or transition state between two stimuli and moments when the user's attention is not focused on any particular stimulus. These states where no SSVEP response should be detected are referred to as the zero class. If stimulation frequencies are located at the alpha band, this could produce false classifications in the resting state. Such problems could easily be avoided by introducing a so-called calibration session for every subject. This methodology was not followed in this contribution, because the BCI realization presented here is fully online, i.e. no calibration data for noise estimation, feature extraction, or electrode selection are needed. The system is ready to use once the subject is prepared.

2.2.5. Adaptive mechanism. In addition to the already applied online adaptation of the MEC method, in which the number of channels used is recalculated every 13 samples (101.5625 ms with the sampling rate of 128 Hz used), the possibility of online adaptation of the time segment length T_s used for classification allows further improvements. Based on our previous work [32], after analysing the distribution of the time segment length for all correct classifications, it was considered that some of the introduced time segment lengths of 750, 1000, 1500, 2000, 3000 and 4000 ms were used very rarely in practice. The three most used time segment lengths over all subjects were 750, 2000 and 4000 ms. Therefore, the used time segment lengths should be limited to these values. The second improvement comes from the idea of simplifying the algorithm: there is no need to use an additional timer, as far as all classifications are performed on the basis of the EEG amplifier used; the new EEG data are transferred to the PC in blocks of 13 samples. Therefore, the new time segment lengths were chosen as 812.5 ms (8 × 13 samples, or 8 blocks of EEG data), 2031.25 ms (20 blocks) and 4062.5 ms (40 blocks). The classification is performed with the sliding window of T_s after receiving the new EEG data block. In the case where no classification can be made and the actual time t allows the extension of the T_s to the next pre-defined value, this new value will be used instead,

$$\forall\, t : T_s = \begin{cases} 8\ \text{blocks} = 812.5\ \text{ms}, & t \leqslant 24\ \text{blocks} \\ 20\ \text{blocks} = 2031.25\ \text{ms}, & 25\ \text{blocks} \leqslant t \leqslant 44\ \text{blocks} \\ 40\ \text{blocks} = 4062.5\ \text{ms}, & t \geqslant 45\ \text{blocks}. \end{cases} \tag{14}$$

In contrast to the previous Bremen BCI system implementations [23, 32], the EEG data are not replaced with zeros after each performed classification. Instead, an additional time for the gaze shifting was included. During this time, the classifier output will automatically be rejected. This could be helpful for many words, when two or more identical commands should be produced consecutively (e.g. three times the command 'right' to reach the letter 'C' in the word 'BCI'). Figure 2 illustrates the changes in the time segment length after classification was carried out.

The next classification could be performed again approximately 914 ms (9 blocks) after the previous classified command. This timing (reset the classifier output for exactly 8 blocks) is a good compromise between the high overall speed of the BCI system and the chance of false classifications caused by movement artefacts during the gaze shifting period. Please note that the five blocks of the EEG data are excluded from the calculations for T_s of 20 and 40 blocks since the reliability of correct command classifications is more important for subjects using these segment lengths.

2.3. Subjects

A total of seven subjects participated in the study. The subjects' mean age was 28.14 years, ranging between 25 and 30 years with a standard deviation of 1.676. For further demographical information, please refer to table 1. This study included two naive subjects, subjects 2 and 3, who had never used any kind of BCI system before. Subject 4 had used the Bremen BCI system once and was known to have a poor performance during the previous experiments. They were included in this study in order to form the basis of comparison. None of the subjects had neurological or visual disorders. Glasses or contact lenses were worn when appropriate. Subjects did not receive any financial reward for participating in this study.

2.4. Experimental setup and data acquisition

The experiments were carried out in a normal office room in the Institute of Automation at the University of Bremen. Subjects were seated in a comfortable chair approximately 80 cm from an LCD monitor (22″ Samsung SyncMaster 2233 with a vertical refresh rate of 120 Hz and resolution of 1680 × 1050 pixels) with the GUI shown in figure 1. Two computers were used. PC1 (notebook) ran the Bremen BCI system, including real-time EEG data acquisition and

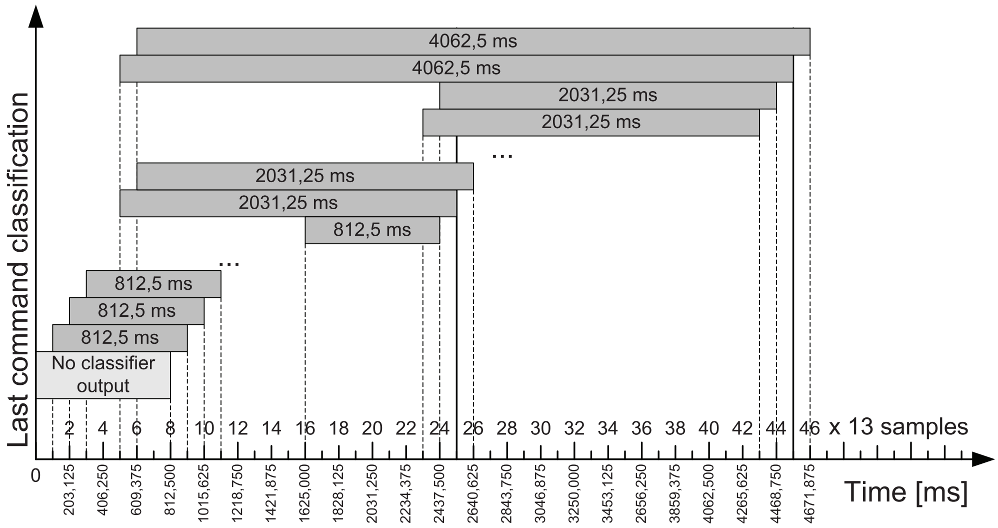

Figure 2. Changes in the time segment length (T_{s_n}) after each performed classification in case no classification can be made at the moment and the actual time t allows the extension of the T_s to the next pre-defined value. The horizontal bars represent the EEG data currently used for classification.

Table 1. BCI spelling performance (spelling time) over all copy spelling words.

			Time [s]					
Subject	Age	Gender	BCI	BREMEN	BRAIN	CORTEX	SIREN	Mean[a]
#1	29	F	13.000	20.008	22.852	31.484	18.180	1.789
#2	29	M	22.953	37.578	47.836	57.586	34.633	3.303
#3	30	F	15.336	35.750	28.742	39.508	25.086	2.448
#4	27	M	95.164	232.375	*	*	106.234	7.383
#5	25	M	17.367	38.594	35.547	49.055	40.117	3.062
#6	29	F	15.641	23.156	20.820	24.274	13.406	1.649
#7	28	F	10.055	15.438	15.336	23.055	12.492	1.295
Mean	28.14		27.07	57.56	28.52	37.49	35.74	
S.D.	1.676		30.287	77.635	11.728	13.862	32.790	

[a] Mean time for correct command classifications for each subject.

classification. The classification results were transmitted via a Transmission Control Protocol/Internet Protocol (TCP/IP) link to PC2 (desktop PC running Linux), which implemented the GUI shown in figure 1. The implementation on two separate PCs was chosen for this study to facilitate meeting the different real-time requirements for the EEG and visual stimulation, although the single PC setup has also been successfully implemented (with adequate multicore hardware) using local TCP/IP for the communication between the two parts [23].

The EEG data were recorded from the surface of the scalp via eight sintered Ag/AgCl EEG electrodes. They are placed on AF_Z for ground, the right ear lobe was used for the reference electrode and P_Z, PO_3, PO_4, O_1, O_Z, O_2, O_9, O_{10} as the input electrodes on the international system of EEG measurement. Standard abrasive electrolytic electrode gel was applied between the electrodes and the skin to bring impedances below 5 $k\Omega$. The impedances were controlled during the subject preparation phase. An EEG amplifier g.USBamp (Guger Technologies, Graz, Austria) was used; 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 (mains frequency in Europe) were applied directly in the amplifier. The amplifier was connected to the USB port of the PC1, a regular dual core notebook computer with a 15.4″ TFT (1280×800) monitor display and Intel Core 2 Duo (2x1.50 GHz) processor running the Bremen BCI software framework under Microsoft Windows XP Pro. The spelling interface of the Bremen BCI was displayed on an external LCD screen (22″ Samsung SyncMaster 2233 with a vertical refresh rate of 120 Hz and resolution of 1680 × 1050 pixels), as shown in figure 1.

2.5. Procedure

Each subject completed a brief questionnaire, including age and gender information, and was prepared for EEG recording. Next, a short familiarization run was carried out in order to introduce the experimental procedures and the letter arrangement to the user. None of the parameters were adapted or changed. The assessment task was to spell five messages with the SSVEP-based Bremen BCI system. All five messages were the same for all subjects and were chosen by the experimenter (copy spelling). The copy spelling words were ‘BREMEN’, ‘BCI’, ‘BRAIN’, ‘CORTEX’ and ‘SIREN.’

The order in which these five terms were presented to the user was determined randomly to avoid adaptations. Each trial ended automatically when the subject correctly spelled the word in question (or when the subject chose to stop spelling due to any reason, such as visual fatigue—this happened with subject 4). Misspellings were to be corrected with the 'Del' option located at the top right of the matrix. The entire session took an average of about 40 min per subject.

2.6. ITR calculation

The ITR calculation leading to the results shown is based on the following formula,

$$B_t = \log_2 N + p \log_2 p + (1 - p) \log_2 \left[\frac{1 - p}{N - 1}\right], \qquad (15)$$

where p is the classification accuracy and N is the number of targets. B_t is calculated in bits per trial. It is important to note that the number of targets in our case is the number of flickering boxes ($N = 5$) and not the number of letters and special characters in the letters layout, because none of the letters and special characters are flickering and therefore they cannot be directly selected by means of an SSVEP communication channel.

In case a wrong moving command was detected, the user should correct this error first, e.g. the correction movement command 'right' after the erroneously selected 'left' command. Thus, in this case the correction step is counted as a correct command classification. Hence the number of commands can increase depending on the subject's performance. In the case of an incorrectly classified selection command, the wrongly spelled letter should be corrected. This results in five additional commands to select the special character 'Del' located at the top-right border of the speller layout.

The classification accuracy p is calculated in the traditional way and is defined as the number of correct command classifications divided by the total number of classified commands. Since all five frequencies can be (erroneously) classified independently of the actual cursor position, it could be assumed that all choices are equally probable, as it is in fact done in the majority of BCI studies.

The spelling time T (for the whole word) is considered in the calculation of the ITR in bits per minute (B_m). This leads to the conventional ITR calculation in bit/min (bpm),

$$B_m = \frac{60}{T} \cdot C_N \cdot B_t, \qquad (16)$$

where C_N is the number of classifications and T is the spelling time in seconds.

The highest theoretically achievable ITR can be roughly calculated as 152.42 bit min^{-1} (assuming the already introduced minimal time between two consecutive command classifications of 914 ms),

$$\mathrm{ITR}_{\max} = \frac{60}{0.914} \cdot \log_2 5. \qquad (17)$$

Since this is the ideal situation, the real ITR values will always be below this theoretical value.

3. Results

Figure 3 shows an example of the copy spelling with the Bremen BCI system. Subject 7 spelled the word 'BCI'. Figure 3(a) presents the EEG signal acquired from the site O_z, figure3(b) the changes in the signal probabilities p_i' as calculated in (12) and figure3(c) the corresponding classifier output. This example was chosen because to spell this word, subject 7 needed the outstandingly short time of only 10.055 s (ITR value of 124 bit min^{-1})! It is important to note that during the time measurement, one sampling block of 13 samples (101.5625 ms) was additionally added at the beginning of the trial. The reason for that is the fact that the EEG amplifier starts to transfer the acquired EEG data in blocks, which cause the shift of EEG data by one EEG block. Many research groups do not consider this time in their calculations, but even though it is negligible, this difference could be decisive during the calculation of the ITR, especially in the range over 100 bit min^{-1}.

Two conventional BCI performances, accuracy and ITR achieved, were averaged over all spelled words and are presented in figure 4. The ITR calculation leading to the results shown is based on the commonly used formula published in [7]. Mean accuracies vary considerably and range from 78.96 (subject 4) to 100.00%. However, the majority of subjects (subjects 1, 3, 5, 6 and 7) completed all copy spelling tasks without errors and achieved mean accuracies of 100%. This means that all five copy spelling words were performed without any errors; all 58 individual command classifications were classified correctly:

- *word BCI* left: 0, right: 4, up: 1, down: 1, select: 3 (9 commands);
- *word BREMEN* left: 2, right: 1, up: 1, down: 2, select: 6 (12 commands);
- *word BRAIN* left: 3, right: 1, up: 1, down: 2, select: 5 (12 commands);
- *word CORTEX* left: 1, right: 4, up: 3, down: 3, select: 6 (17 commands);
- *word SIREN* left: 1, right: 1, up: 1, down: 1, select: 5 (9 commands);
- *Total* left: 7, right:11, up: 7, down: 9, select: 25 (58 commands).

Since all of these 58 command classifications are true positives, the false positive rate cannot be calculated and the ROC curve is not provided.

Figure 4(b) presents the normalized (by the total number of correct classifications) distribution of the time segment length. This distribution is independent of the stimulus frequency. It is important to note that even for the subject with the worst ITR (subject 4), a time segment length of 813 ms was sometimes successfully used for a correct classification of the intended frequency. Subject 4 experienced visual fatigue and discomfort, and aborted the experiments after spelling three randomly chosen copy spelling words.

Table 1 shows the times spent in individual spelling tasks as well as the mean (Mean) and standard deviation (SD) for each measured variable. Since subject 4 finished only

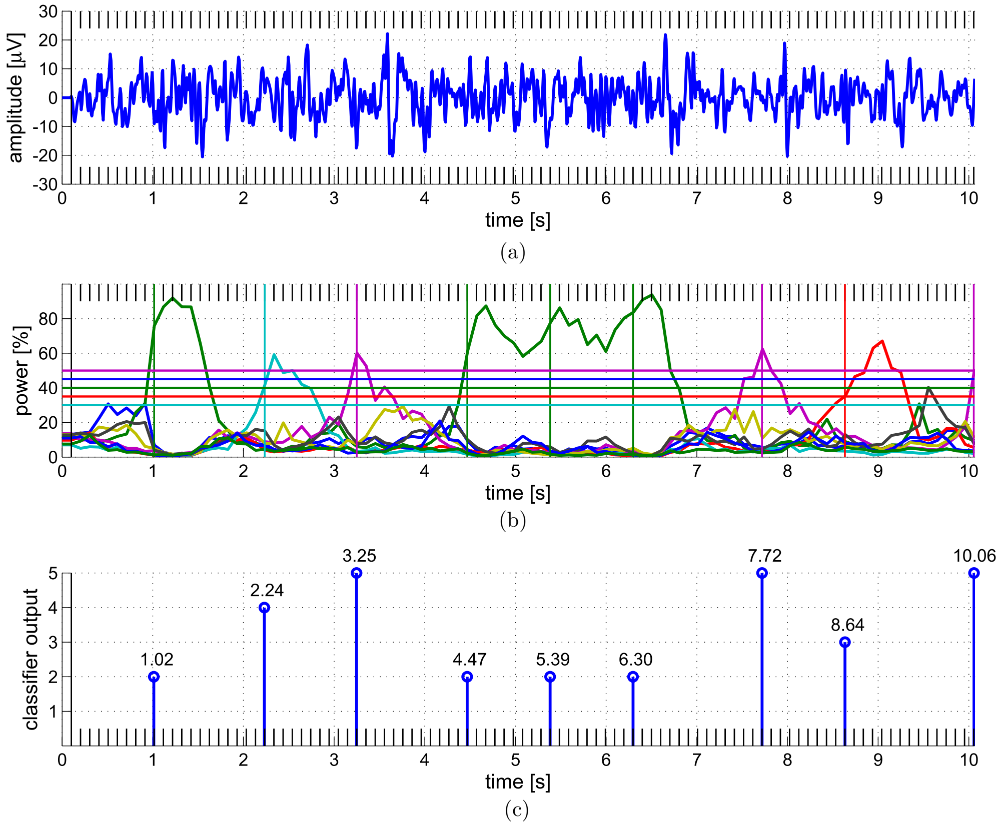

Figure 3. Spelling with Bremen BCI in the example of subject 7 and the copy spelling word 'BCI'. The classifications were performed every 13 samples; these moments are marked with stroke lines on the x axes in the diagrams. (a) Example of the EEG signal acquired from site O_z (one of the eight electrodes used in this study). (b) Signal classification on the basis of different thresholds β_i ranged from 30 to 50%. Each colour corresponds to the individual stimulating frequency and the related threshold β_i. (c) Classifier output.

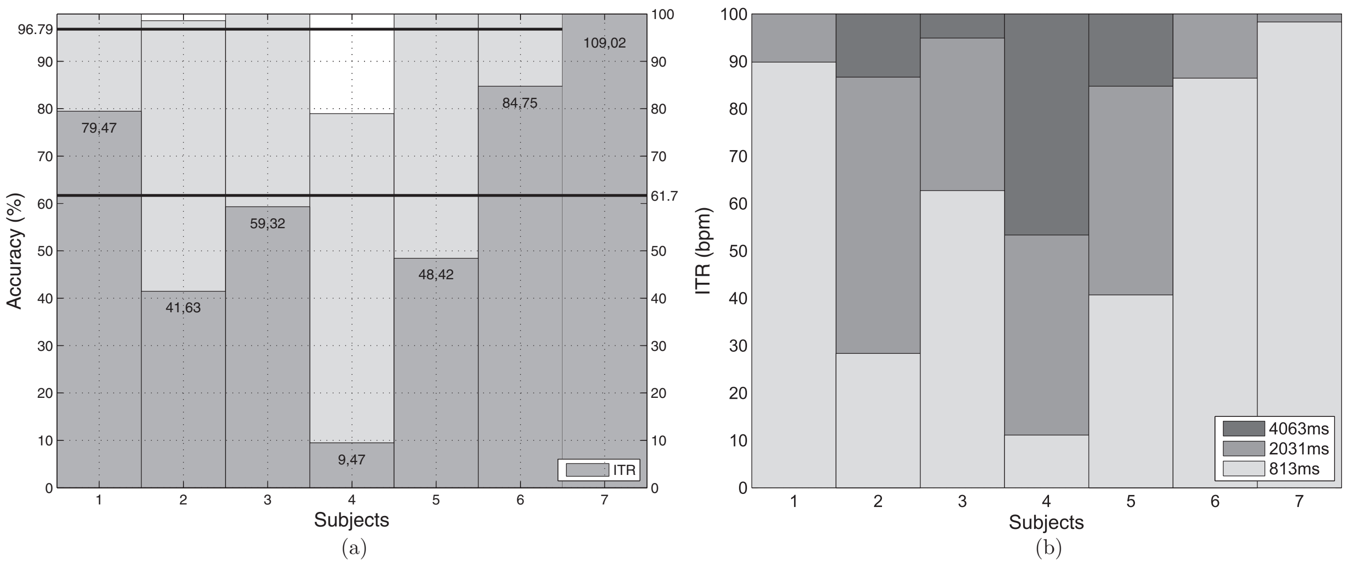

Figure 4. Results over all subjects. (a) Mean individual accuracies and information transfer rates. (b) Distribution of the time segment length for all correct classifications.

three copy spelling tasks, the missing values are represented by stars in this table. Furthermore, the mean times for all correct classifications over all words were calculated for each subject and are presented in the last column of the table. These times are measured between the actual correct command classification and the previous command classification, and give a good value for comparison in addition to the commonly used performance indicator ITR in bit min^{-1}.

Two supplementary videos were recorded separately (the results are not included in this paper) that demonstrate the high online performance of the SSVEP-based Bremen-BCI system, and also provide a better explanation of the experimental protocol for spelling two words, i.e. BREMEN and BCI. These are available at stacks.iop.org/JNE/8/036020/mmedia.

4. Discussion

The brain–computer interface is a relevant and exciting topic in neuroscience and biomedical engineering. Current developments have led to an improvement in the main components of BCIs, such as data acquisition and signal processing. However, in order to make BCIs practical devices for a wide group of users with communication deficits in real-world settings, BCI accessibility, flexibility and usability must be substantially improved. High ITRs are essential for a BCI to achieve these goals.

The highest mean ITR for healthy subjects using a SSVEP-based BCI reported so far is 92.8 ± 14.1 bit min^{-1} for code-based modulation [19]. These ITR values are not directly comparable to the actual study based on frequency modulation due to different types of modulation, but they give a good indication of the range attainable. In the study presented here, the overall mean ITR over all spelled words was 61.70 ± 32.676 bit min^{-1} with a mean accuracy of 96.79 ± 7.881%. Considering only the subjects who finished the complete experiment, these values increased (ITR: 70.41 ± 25.390 bit min^{-1}, accuracy: 99.76 ± 0.583%). Although these values are lower than the reported ITR in [19], these results are promising, because of the very high accuracy for the majority of subjects. Five of the seven subjects completed all copy spelling words without errors, achieving a mean accuracy of 100%, as shown in figure 4(a). In addition, the highest peak ITR and mean ITR for a single subject in this experiment were 124.00 and 109.02 bit min^{-1}, respectively (subject 7). It is worth mentioning that this peak ITR value of 124 bit min^{-1} is higher than all values previously published in the literature for any kinds of BCI paradigms. The improvements in the SSVEP signal processing, the introduction of the novel adaptive time segment length and the new type of online visual feedback to the user were the keys to achieving good online performance. In comparison to the original method [25] with the previous mean ITR of 27 bit min^{-1}, a mean ITR of 61.70 bit min^{-1} was achieved in the study presented here. It is important to note that this system realization is fully online, i.e. no calibration is performed prior to the online experiment. In addition, including such a calibration session may overcome the problems of the poor performance of subject 4. For this subject, it could be recommended to change the stimulating frequencies and to adapt the fixed thresholds β_i. Another approach could be the use of the BCI wizard [34], which will automatically identify and optimize important parameters not only for some specific BCI paradigm but across different BCI approaches.

The conventional calculation of the BCI performance in bit min^{-1} is directly dependent on the time and the number of targets. There are also two ways to achieve a high ITR: (1) by decreasing the time required for single command classifications and (2) by increasing the number of detectable targets (this way is easier, in general). The traditional formula introduced in [7] has no limitations—if only one command is transferred over the communication channel, it is possible to calculate the ITR. In the case of an experimental protocol with many targets and the goal to classify just one of them, a very high ITR could be achieved after this first selection, even if this command will need a comparatively long time to be produced. Furthermore, the possibility of wrong classifications cannot be fully excluded—this one classification could just be a false positive! This was one of the reasons why table 1 reports the mean times in *s*, and not the ITRs in bit min^{-1}. This problem of the ITR calculation is not new; the recent paper from Shyu *et al* [14] has already introduced the mean times for command classification (called CTI—command transfer interval). In real-world applications, BCI users with several disabilities often just need to send 1 bit of information at the right time in order to initiate an autonomous sequence e.g. such as ‘pour a drink’ [35]. In the study presented here, the mean values of time for correct classifications ranged between 1.295 and 7.383 s. As with the previous study with the Bremen BCI speller [26], a difference between the times required for the classification of individual commands (i.e. stimulating frequencies) was found. These differences seem to be influenced by the selection of the thresholds β_i. Again, it could be expected that an additional calibration run for adjusting subject-dependent parameters could greatly improve BCI performance, especially in terms of BCI accuracy for lower performing subjects.

This study has been carried out without any free spelling words. The reason for this is the fact that in the case of free spelling, the strong comparison test with the current letter’s arrangement presented in figure 1 is impossible, as the choice of words to be spelled is very subject dependent. During our previous studies [22, 23], we realized that some users tended to select shorter words when all letters are located close to the initial letter ‘E’ on the layout. On the other hand, other subjects were prone to select ‘complicated words’ with rare letters located at the layout boundaries. It is important to repeat that the number of targets in the current SSVEP-based BCI speller application is the number of flickering boxes ($N = 5$) and not the number of letters and special characters in the letters layout, because none of the letters and special characters are flickering and therefore they cannot be directly selected by means of an SSVEP communication channel. Therefore, the individual words spelled are not important. The last column in table 1 presents the mean time (also called CTI), which is independent of the words spelled.

5. Conclusion and future work

In this paper, the results of the evaluation of the updated Bremen BCI in online BCI experiments with seven healthy volunteers have been presented. These results demonstrate that improvements in the signal processing and feedback modules of the BCI system constituted the basis for achieving an information transfer rate in the range of 100 bit min^{-1}. Particularly important is the improvement in the BCI accuracy. Five out of seven subjects spelled all copy spelling words without errors. The adaptive time segment length and the novel type of visual feedback were the keys to achieving a high online performance.

Further research should identify other factors that can influence performance, such as human factors, training procedures, time behaviour of the complete system (the user can learn the time latencies and responses of the system), and error recognition and error correction at early stages of the BCI signal processing. Subject-specific parameter adaptation seems to be unavoidable in order to achieve further progress in terms of information transfer rate, classification time and accuracy with a broader population of users.

In this work, the classification thresholds (β_i) were determined based on our previous work (offline analysis of EEG data collected during previous studies with many subjects) [22–24]. Further research might also consider a general method to automatically determine the individual constants for each subject in order to take into account the variation in the power of SSVEPs at different frequencies.

Additionally, water-based or dry EEG electrodes should be considered to make BCI systems less annoying. Our recent study presents the first results of the evaluation of water-based electrodes in the online BCI experiments with ten healthy subjects [20].

Acknowledgments

The author gratefully acknowledges the important contributions of Dr Ola Friman, Dr Hubert Cecotti and Diana Valbuena to prior versions of Bremen-BCI softwave. The research leading to these results has received funding from the European Community's Seventh Framework Programme under grant BRAIN, no 224156, and from a Marie Curie European Re-Integration Grant RehaBCI, no 224753.

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