J. Neural Eng. **4** (2007) L23–L29 doi:10.1088/1741-2560/4/4/L01

LETTERS AND COMMENTS

Self-initiation of EEG-based brain–computer communication using the heart rate response

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Received 20 July 2007
Accepted for publication 5 November 2007
Published 27 November 2007
Online at stacks.iop.org/JNE/4/L23

Abstract
Self-initiation, that is the ability of a brain–computer interface (BCI) user to autonomously switch on and off the system, is a very important issue. In this work we analyze whether the respiratory heart rate response, induced by brisk inspiration, can be used as an additional communication channel. After only 20 min of feedback training, ten healthy subjects were able to self-initiate and operate a 4-class steady-state visual evoked potential-based (SSVEP) BCI by using one bipolar ECG and one bipolar EEG channel only. Threshold detection was used to measure a beat-to-beat heart rate increase. Despite this simple method, during a 30 min evaluation period on average only 2.9 non-intentional switches (heart rate changes) were detected.

1. Introduction

A brain–computer interface (BCI) is a technical communication system which transforms mentally induced brain signal changes (electric, magnetic or metabolic) into a control signal within milliseconds or seconds, depending on the brain signal used (for a review, see [1–3]). One type of input signal is steady-state visual evoked potentials (SSVEPs) recorded from scalp electrodes placed over the occipital area [4–7]. Shifting the gaze, or simply shifting the visual spatial attention without moving the eyes [8], on a flashing light source evokes SSVEPs of the corresponding flickering frequency in the visual cortex including sub and higher harmonics [9].

One important issue for BCI systems, in order for them to become practical assistive devices, is self-initiation. In other words, each time a user needs BCI-based communication, he/she should be able to switch the system on and off autonomously. For this purpose, patients usually need the assistance of other people. First results, however, show that severely paralyzed patients can learn to self-initiate a BCI by operant feedback training and by classifying the slow cortical potential shift [10].

It is of interest to investigate whether signals not recorded directly from the brain, but modulated by brain activity, such as, for example, the heart rate (HR), can be used for the self-initiation of a BCI. The heart has a constant intrinsic rhythm with a period of about 1 s, which is modulated especially by respiration, blood pressure waves and 'central commands' [11]. This means that central processes, such as, for example, motor preparation, mental simulation, stimulus anticipation and translation, can result in a HR response [12–18]. If such a centrally induced HR response can be detected in the ongoing ECG signal, it can be used to switch on/off a BCI. Following a preliminary test with three subjects [19], here we report on the online detection of the respiratory HR response, induced by brisk inspiration, and SSVEP-based control of a prosthetic hand in a group of ten healthy subjects.

This work is subdivided into two parts. In the first part, an off-line investigation, the threshold detection of transient HR changes is analyzed with respect to usability as a toggle switch. Furthermore, for each subject, from a predefined frequency

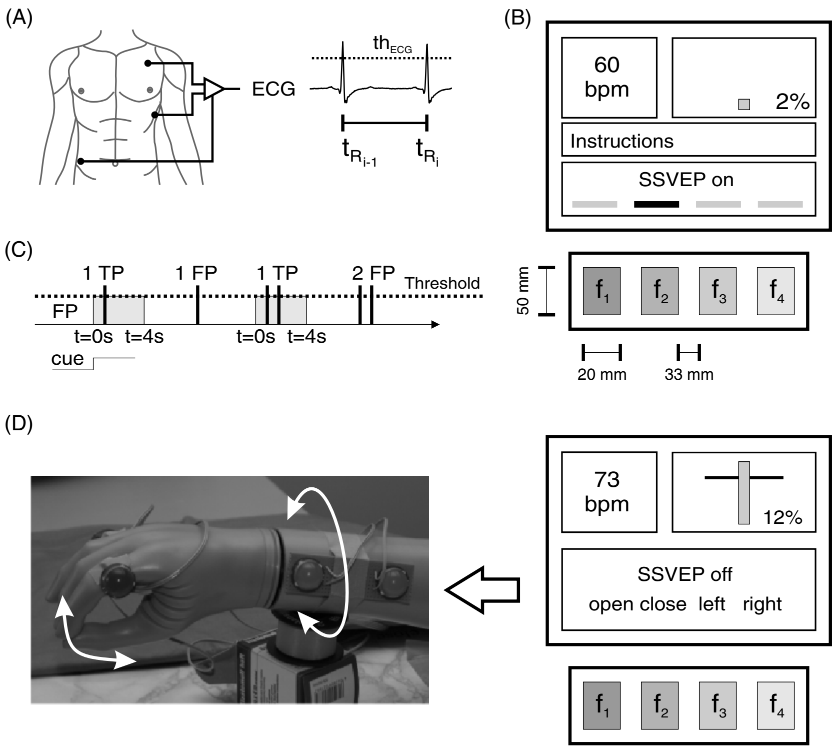

Figure 1. (A) ECG electrode placement and R-peak detection. (B) Data collection. The upper part of the screen provided information on the instantaneous heart rate IHR_i in bpm (left) and relative changes $\Delta\mathrm{IHR}_i$ (right). Instructions for the subjects were presented in the middle part of the screen. In the lower part cue information for SSVEP feedback experiments was provided. The SSVEP stimulation unit, composed of four LEDs each flickering at a different frequency ($f_1, \ldots, f_4$), was positioned beneath the screen. (C) Definition of TP/FP periods for ROC analysis. (D) Online experiment. IHR_i and $\Delta\mathrm{IHR}_i$ were presented on the left and right sides, respectively. The bold horizontal line in the $\Delta\mathrm{IHR}_i$ window indicates to the on/off toggle switch threshold $\mathrm{th}_{\mathrm{hit}}$. In the lower part of the screen the current status of the SSVEP-based BCI (on/off) and the detected command for the prosthetic hand were shown. The prosthetic hand was placed on the left-hand side of the screen.

set, the most reactive SSVEP-stimulation frequencies were identified. The second part presents the results of an online feedback experiment. Subjects had the task of operating a prosthetic hand by self-initiating the BCI and executing a predefined movement sequence by means of SSVEPs.

2. Methods

2.1. Subjects and data acquisition

Ten healthy subjects (seven male, three female, age 27 ± 5 years, right handed) participated in this study which was conducted according to the declaration of Helsinki. The subjects had normal or corrected to normal vision and were seated approximately 0.5 m from the computer screen and stimulation unit (SU). The SU, an independently working self-constructed device mounted below the screen, was composed of four red light-emitting diodes (LED), each flickering at a different frequency [20].

Continuous EEG signals were recorded bipolarly from sintered Ag/AgCl electrodes placed over the occipital cortex (2.5 cm anterior and posterior to electrode position O2, ground Fz, international 10–20 system), filtered between 0.5 and 100 Hz (Notch filter at 50 Hz) and digitized at a rate of $fs = 256$ Hz. Simultaneously the ECG was recorded from the thorax, filtered between 0.01 and 100 Hz (Notch at 50 Hz) and sampled at fs (figure 1(A)). ECG electrodes (sintered Ag/AgCl) were placed on the thorax at the level of axilla and below the last rib (ground right hip, figure 1(A)).

The recording equipment consisted of one 16-channel amplifier (gBSamp, Guger Technologies, Graz, Austria), one data acquisition card (E-Series, National Instruments Corporation, Austin, USA) and a standard personal computer running Windows XP (Microsoft Corporation, Redmond, USA). The open source packages BIOSIG [21] and rtsBCI [22], both based on MATLAB/Simulink (MathWorks, Inc., Natick, USA) in combination with the Real-Time Windows Target and Real-Time Workshop, were used to store and process the data in real-time, and for feedback generation.

2.2. Feature extraction and classification

2.2.1. Transient heart rate changes. The instantaneous heart rate (IHR_i) was computed by the detection of beat-to-beat intervals in the ECG. Simple threshold detection ($\mathrm{th}_{\mathrm{ECG}}$) was used to identify the R-peak (R-wave) of the QRS complex. As a characteristic point from each segment exceeding $\mathrm{th}_{\mathrm{ECG}}$ the maximum value at time t_{R_i} was selected (figure 1(A)). The resulting IHR_i in beats per minute (bpm) was computed according equation (1). Transient IHR_i changes ($\Delta\mathrm{IHR}_i$) were calculated according equation (2). Each time the $\Delta\mathrm{IHR}_i$ increase, induced by brisk inspiration, was higher than a subject-specific value (th_{hit}), an on/off (off/on) state switch of the SSVEP-based BCI was triggered. After each switch, no other switch command was accepted for a period of 3 s (refractory period):

$$\mathrm{IHR}_i = 60/\left(t_{R_i} - t_{R_{i-1}}\right) \tag{1}$$

$$\Delta\mathrm{IHR}_i = 100 \cdot (\mathrm{IHR}_i - \mathrm{IHR}_{i-1})/\mathrm{IHR}_{i-1}. \tag{2}$$

2.2.2. SSVEP. The power density spectrum (PSD) of the past 1 s EEG segment was estimated every 250 ms by means of a $4 \cdot fs$-point-discrete Fourier transform (DFT, zero-padding, rectangular window, PSD frequency resolution $\Delta f = 1/(4 \cdot fs) = 0.25$ Hz). The three spectral components $(f_i - \Delta f, f_i, f_i + \Delta f)$ around each stimulation frequency (e.g. 6.00, 6.25 and 6.50 Hz at a stimulation frequency of $f_i = 6.25$ Hz) as well as for the second and third harmonics were averaged, summed up and weighted. Weighting was necessary to level higher and lower power spectrum values due to the $1/f^{\alpha}$ scaling of the EEG power spectral density (decrease in log power with increasing log frequency) [23]. The weighting coefficients were computed from a 60 s EEG segment where subjects were not focusing on the flickering lights. The flickering light source with the highest weighted sum was selected if detected continuously for a predefined period of time ($N_d \cdot 250$ ms, with N_d being the number of continuous detections) (harmonic-sum-decision classifier, HSD [7, 20]). To increase the robustness of SSVEP detection, i.e. to reduce the number of false positive activations, in this study the parameter N_d was defined for each subject individually. Each detection triggered a corresponding prostetic hand movement followed by a refractory period of 8 s (the duration of movement execution).

The method of inverse filtering was applied to detect muscle artifacts by estimating the autoregressive parameters of EEG without artifacts [24]. Autoregressive parameters are considered the coefficients of a digital filter. Applying the filter inversely (inverted transfer function) to the recorded EEG provides a white noise process. Any superimposed EMG artifact increases the root mean square (RMS) of the inversely filtered process [25]. Here, each time the value exceeded 5RMS from the artifact-free EEG the BCI suspended working (‘freeze’ mode). Only after 1 s of artifact-free EEG the BCI resumed working. To set up the filter coefficients at the beginning of each session 60 s of artifact-free EEG was recorded [25].

2.3. Off-line investigation

2.3.1. Data collection. To examine the IHR_i ($\Delta\mathrm{IHR}_i$) variability and find reactive SSVEP-frequencies to operate the prostetic hand, the following datasets were recorded.

- *Cue-based brisk inspiration (CBI).* Four cue-based training runs ($\mathrm{CBI}_{1,2,3,4}$) with 20 trials of brisk inspiration each were recorded. At $t = 0$ s of each trial a cross was displayed in the middle of the screen and a warning tone was presented. Subjects were instructed to take a brisk breath after cue presentation at $t = 1$ s (arrow pointing upwards). At $t = 6$ s the screen was cleared and a randomly selected inter-trial period between 4 s and 17 s was added before the next trial started.
- *Periods of rest and tasks of everyday life (TEL).* One 15 min dataset, subdivided into 1 min of rest, 5 min of reading aloud a newspaper, 3 min of rest, 3 min of small talk with the experimenter and another 3 min of rest, was recorded. The instructions were presented on the computer screen (see figure 1(B)). During rest, subjects were instructed to sit relaxed and calmly.
- *SSVEP feedback experiments.* Eight feedback training runs with 40 trials each (10 per flickering light source) were performed. The trial duration was 6 s. Subjects were instructed to focus on the light source according to the cue (figure 1(B)), a marker (horizontal line) placed above the light source to focus, shown from $t = 2$ s to $t = 6$ s. Additionally at $t = 2$ s a beep was presented. At $t = 6$ s a high warning tone was presented each time the detected SSVEP and cue were corresponding. $N_d = 4$ was selected as the default value for SSVEP detection. The order of appearance of the cues was randomized. Preliminary investigations showed that individual subjects have different reactive SSVEP frequencies. Therefore each subject performed the feedback experiments with two different sets of flickering frequencies. For the first four runs ($\mathrm{SSVEP}_{1,2,3,4}$) frequencies of $f_1 = 6.25$, $f_2 = 7.25$, $f_3 = 8.00$ and $f_4 = 13.00$ Hz (frequency set LOW) were used; runs 5–8 ($\mathrm{SSVEP}_{5,6,7,8}$) were performed using $f_1 = 11.75$, $f_2 = 13.00$, $f_3 = 15.25$ and $f_4 = 17.25$ Hz (frequency set HIGH).

The datasets were recorded in the following order: CBI_1, SSVEP_1, SSVEP_2, SSVEP_3, SSVEP_4, CBI_2, SSVEP_5, SSVEP_6, SSVEP_7, SSVEP_8, CBI_3, TEL, and finally CBI_4. Before SSVEP_1 and SSVEP_5 60 s data were recorded ($\mathrm{INIT}_{1,2}$) to set up the weights for the HSD [20].

2.3.2. Off-line analysis and online simulation. The subject-specific R-peak detection threshold th_{ECG} was defined as 80% of the smallest R-peak amplitude in dataset CBI_1. The amplitude was identified by visual inspection of the data. Before further analyses were carried out, R-peak detection was applied to the remaining datasets and the correctness of the detections was checked. No erroneous detections were found.

To estimate the performance of the threshold detector th_{hit} receiver operating characteristics (ROC) analysis was applied to the first two cue-based training runs without feedback ($\mathrm{CBI}_{1,2}$). By depicting the tradeoff between true positive (TP) detections and false positive (FP) activations, ROC analysis is useful for selecting classifiers based on their performance [26]. In this work the best possible threshold for classification was selected. A TP detection was counted each time $\Delta\mathrm{IHR}_i$ (beat-to-beat based) exceeded the th_{hit} at least once within the 4 s period following the cue (from $t = 0$ s to $t = 4$ s). Each exceeding of th_{hit} outside this period was counted as one FP detection (figure 1(C)). The ROC graph was generated by varying the researched th_{hit} from $\Delta\mathrm{IHR}_i = -100\%$ to

Table 1. Off-line investigation. The mean IHR_i before (ref) and mean maximum ΔIHR_i (max) after cue-based inspiration ($CBI_{1,2,3,4}$), the averaged SSVEP classification accuracies for the two stimulation frequency sets (LOW and HIGH) and the selected off-line ΔIHR_i detection threshold th_{hit} with corresponding TP, FP and prediction rate PR = TP/(TP+FP) for training (TP_{tr}, FP_{tr}, PR_{train}) and online simulation (TP_{sim}, FP_{sim}, PR_{sim}) dataset are presented for each subject (Id).

	$CBI_{1,2,3,4}$		SSVEP		Off-line ROC analysis						
Id	ref bpm	max %	LOW %	HIGH %	th_{hit}	TP_{tr} no.	FP_{tr} no.	PR_{tr}	TP_{sim} no.	FP_{sim} no.	PR_{sim}
s0	80.3	10.1	36.9	44.4	39.1	1	1	0.50	0	17	0.00
s1	77.6	9.2	41.3	46.9	13.1	7	1	0.88	12	23	0.34
s2	72.5	15.2	88.1	85.0	8.5	35	1	0.97	38	51	0.43
s3	84.6	3.8	77.5	68.8	5.9	21	1	0.95	20	198	0.09
s4	68.9	10.9	48.9	45.0	7.5	34	1	0.97	33	113	0.23
s5	68.8	9.6	46.3	40.6	19.4	2	2	0.50	1	17	0.06
s6	65.9	7.9	59.4	67.5	82.3	3	2	0.60	0	2	0.00
s7	74.5	16.3	34.4	74.4	10.0	33	1	0.97	37	117	0.24
s8	89.4	5.8	35.6	51.9	4.8	5	1	0.83	22	128	0.15
s9	55.2	12.4	46.3	61.3	16.0	5	1	0.83	6	1	0.86
$\bar{x}$		10.1	51.5	58.5		16.1	1.2	0.80	18.8	72.2	0.24

ΔIHR_i = +100% in steps of 0.1%. For each step the numbers of TP and FP detections were calculated.

The th_{hit} with the lowest number of FP and at the same time the highest number of TP detections was selected and threshold detection was applied to the remaining datasets $CBI_{3,4}$, TEL and $SSVEP_{1,2,3,4,5,6,7,8}$ (online simulation).

2.4. Online experiment

The duration of the feedback experiment, recorded on a different day, was about 1 h. During the first approximately 20 min subjects could get familiar with the system and subject-specific parameters were fine-tuned. At the beginning 60 s of data were recorded to set up the weighting coefficients for the averaged spectral components, to compute the inverse filter coefficient for EMG detection and the R-peak detection threshold th_{ECG} (80% of the amplitude of the smallest R-peak). For each subject the LEDs of the SU were blinking with the frequency set (LOW or HIGH) identified during the screening experiment. The first issue was to adapt th_{hit}. Subjects were instructed to switch on/off the SSVEP-based BCI by brisk inspirations. In doing so, th_{hit} was decreased/increased (the starting value was th_{hit} = 10%; see the mean $\bar{x}$ of column max in table 1) in order to reduce FP activations during periods of non-control (about 60 s). At the same time, however, subjects needed to be able to voluntarily switch the SSVEP-based BCI on/off. The second issue was to find N_d in a way to obtain reliable classification when focusing the flickering lights. Subjects were also instructed to focus the middle of the screen for 20 s. During this period no FP SSVEP detection was allowed. The value for N_d was stepwise incremented by 1 starting from $N_d = 4$ (1 s). All identified values were fixed for the rest of the experiment.

The evaluation of the system consisted of one 30 min recording. Subjects were instructed to switch on the SSVEP-based BCI according the verbal instruction (start command) from the experimenter, execute a predefined sequence with the prosthetic hand, and turn the BCI off again. The following sequence had to be performed: hand open (O), turn left (L), turn right (R), close hand (C), R, O, C and L. A modified hand prosthesis (Otto Bock Austria, Vienna, Austria) was used for the experiment. Additional to the available hand open/close grasp function, a wrist rotation was incorporated [20]. The prosthetic hand was working in the 'error ignoring' mode and was consequently accepting only the predefined command sequence. The aim was to repeat the whole procedure four times. The timing of the instructions was randomly chosen by the experimenter, who was talking and interacting with the subjects during periods of non-control (e.g. handing a glass of water to drink). The hand sequence had to be performed as fast as possible. The feedback screen presented to the subjects is shown in figure 1(D).

3. Results

3.1. Off-line investigation

The results of the off-line investigation are summarized in table 1. Cue-based brisk inspirations (runs $CBI_{1,2,3,4}$) resulted in an average ΔIHR_i increase of 10.1%. For each subject the mean heart rate IHR_i in the 3 s interval before cue presentation and maximum ΔIHR_i changes within the 4 s period following the cue are shown in columns ref and max, respectively. SSVEP-feedback runs $SSVEP_{1,2,3,4}$ with the low frequency set (column LOW) achieved an average classification accuracy of 51.5%; the performance of the high frequency set (column HIGH) was 58.5%.

The results of the ROC analysis are summarized in the remaining columns. The selected detection threshold th_{hit}, corresponding TP, FP and prediction rate PR = TP/(TP+FP) for the training ($CBI_{1,2}$) and simulation dataset are presented. For the training dataset the average number of TP detections was 16.1 (out of 40.0, 40.3 %) with 1.2 (0.16%) FPs and a corresponding mean PR of 0.80. The mean number of true negative (TN) heart beats for each subject was 772.6. The average area under the ROC curve was 0.98. Due to the unbalanced ratio between TP and FP a value close to 1.0 was expected. The average TP, FP and PR for the simulation dataset were 18.8, 72.2 and 0.24, respectively; the mean TN number of heart beats for each subject was 4226.3.

3.2. Online experiment

Each subject succeeded in switching on and off the system by transient IHR_i changes induced by brisk inspirations and operate the prosthetic hand by means of SSVEP.

Figure 2 gives an overview of the 30 min feedback experiment. System parameters and online results are summarized in table 2. In total the paradigm required eight ΔIHR_i-triggered BCI state switches (four times on and four times off). Seven subjects successfully performed four times the prosthetic hand movement sequence. Due to a time-out three subjects were not able to finish the fourth sequence (column TP). The average number of FN detections, i.e. the number of brisk inspirations which erroneously were not detected, was 4.9. The mean/median number of FP detections during the 30 min experiment was 2.9/2.0. After each FP detection, subjects were instructed to switch the BCI system off again. With 8 TP, 1 FN and zero FP subject s4 achieved the best performance. The mean prediction rate PR = TP/(TP+FP) was 0.76. The average mean/median duration in seconds needed for each switching operation was 37/12 s.

Column Cl shows the number of SSVEP classes subjects were able to elicit and use for control. For subject s5 only two out of the four flickering light sources could be detected; for subject s4 only three out of four. The overall mean numbers of correct SSVEP detections (CD), wrong detections (WD) and corresponding performance index PI = CD/(CD+WD) were 30.1, 12.9 and 0.72, respectively. Without considering subjects s4 and s5 the values were 29.6, 11.3 and 0.74. The minimum time needed to complete one movement sequence was $t_{\min} = (N_d \cdot 0.25 + 8) \cdot 8\text{s}$. For $N_d = 6$ the resulting $t_{\min} =$ 76 s. With the mean $N_d = 6.2$ the maximum selection speed was 1 command every 9.55 s or 6.3 commands per minute. Without considering subjects s4 and s5, the mean number of erroneous detections was 11.3. Consecutively the error rate for each of the four movement sequences was err $= 11.3/4 \approx 2.8$. This means that with a mean/median time of 180/168 s for one sequence one wrong SSVEP detection occurred every 64.3 s/60.0 s.

4. Discussion

The aim of this work was to investigate whether transient heart rate changes ΔIHR_i can be used as an additional information channel in BCI research. Here a toggle-switch was implemented and used to turn on and off a SSVEP-based 4-class BCI.

The results of the cue-based inspirations experiments $CBI_{1,2,3,4}$ show, as one could expect, that brisk inspiration causes an increase of the IHR_i. On average over ten subjects an increase of 10.1% was found compared to the 3 s reference period prior to cue presentation.

The cue-based SSVEP feedback experiments confirmed the need of finding subject-specific reactive SSVEP-stimulation frequencies. Compared to the LOW frequency

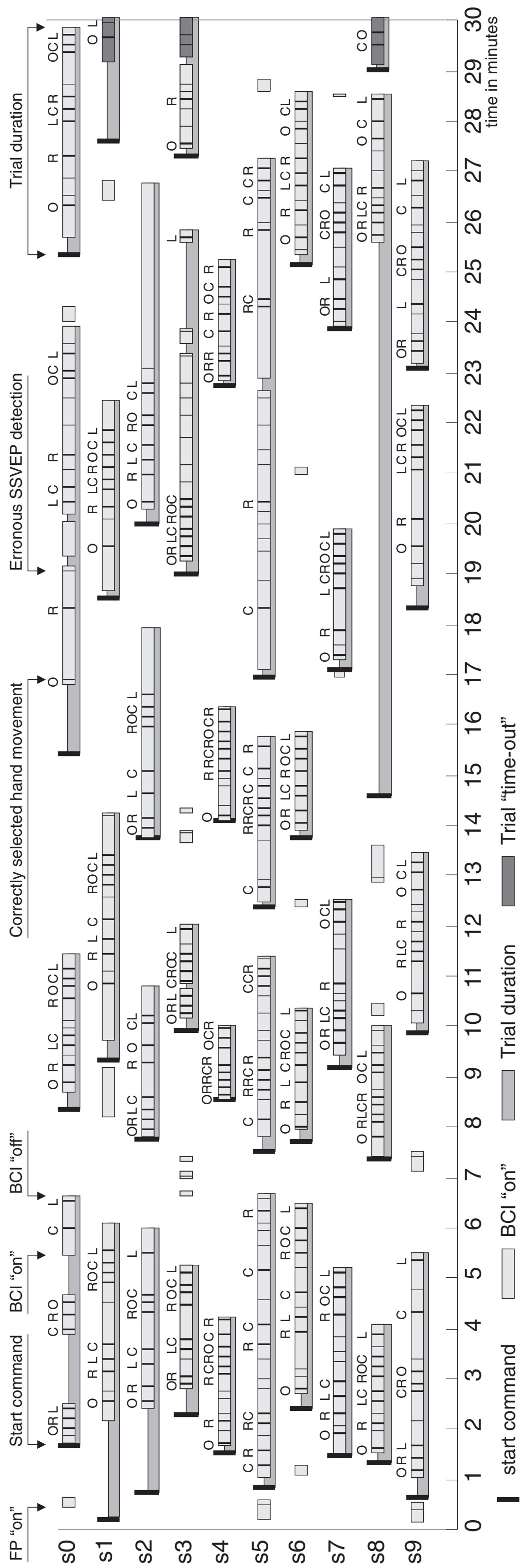

Figure 2. Schematic overview of the feedback experiment. Gray areas show the duration of each trial. After each start command (bold vertical line), subjects had to switch on the BCI (on-state colored in light gray) and to perform a predefined movement sequence with the prosthetic hand (commands: open (O), close (C), turn left (L) and turn right (R)). Markers during BCI ‘on’-state represent times of SSVEP selection; letters above indicate correct selections. Activations outside the trial duration period are false positive detections.

Table 2. Online experiment. The identified detection threshold th_{hit}, the number of consecutive SSVEP detections N_d, the number of TP, FN and FP detections, and prediction rate PR = TP / (TP + FP) for self-initiation with corresponding mean/median duration in seconds (mn/md, column 5), the number of correct SSVEP detections CD , wrong detections WD and the performance index PI = CD/(CD + WD), the mean/median time needed to trigger a movement (mn/md, column 12) and the used number of SSVEP classes are summarized for each subject (Id).

		Self-initiation						SSVEP				
Id	th_{hit}	N_d	TP	FN	FP	PR	mn/md	CD	WD	PI	mn/md	Cl
s0	10	4	8	8	6	0.57	31/21	32	12	0.73	185/175	4
s1	15	8	7	7	2	0.78	61/59	25	7[a]	0.78[a]	206/202	4
s2	20	10	8	10	0	1.00	32/12	32	1	0.97	162/160	4
s3	25	6	7	5	9	0.44	20/16	26	18[a]	0.59[a]	173/139	4
s4	15	5	8	1	0	1.00	4/4	32	9	0.78	126/134	3
s5	23	5	8	0	3	0.73	12/11	32	30	0.52	322/259	2
s6	20	6	8	2	3	0.73	13/13	32	11	0.74	163/161	4
s7	23	6	8	2	2	0.80	7/7	32	13	0.71	184/183	4
s8	9	6	7	11	2	0.78	170/9	26	10[a]	0.72[a]	145/141	4
s9	15	6	8	3	2	0.80	17/19	32	18	0.64	219/214	4
$\overline{x}$		6.2	7.7	4.9	2.9	0.76	37/12	30.1	12.9	0.72	188/168	
$\overline{x_{s4,s5}}$								29.6	11.3	0.74	180/168	

[a] Time out.

set, the HIGH frequency set revealed an overall improved classification accuracy of 7%. In one subject (s7) this increase of classification accuracy was even 40%.

For the off-line analysis the ΔIHR_i detection threshold th_{hit} was selected in such a way as to maximize the number of TP and at the same time to minimize the number of FP detections. One possible consequence of these strict selection criteria is a low number of TP. When applying selected th_{hit} to the remaining data and computing an online simulation on average 18.8 (46.9%) TP were detected. At the same time the overall FP rate was 72.2 (1.59%). This TP rate was higher than the TP rate of 16.1 (40.3%) of the training data. The reason was that since the subjects were sitting relaxed and calmly in front of the computer screen, the IHR_i decreased over time. This decrease, however, increased the number of FP detections. One possible option to overcome this problem is to provide additional information to the classifier, e.g. a combination of IHR_i and ΔIHR_i. During the online experiment we did take care about this fact by choosing the largest possible th_{hit} value for each subject.

After only 20 min of parameter setup and subject training by means of one bipolar EEG and one bipolar ECG channel, subjects were able to self-initiate and operate the SSVEP-based BCI. Of interest is that during relatively long periods (minutes) when no control was intended, only a mean/median of 2.9/2.0 false positive ΔIHR_i was detected. The aspect of relative insensitivity from verbal interactions and muscle activity (e.g. drinking a glass of water or talking during the experiment) is an important issue. The results show that subjects with higher ΔIHR_i changes in the cue-based inspiration task achieved better self-initiation results than the others. This value therefore seems to be a performance predictor. The number of FN detections across subjects varied between 0 and 11. Mostly the cause of misclassification was related to the simple detection method used. The ΔIHR_i increase did not occur from beat to beat, but was achieved after 2 beats (e.g. instead from 60 bpm to 74 bpm, first from 60 bpm to 68 bpm and then from 68 bpm to 74 bpm; th_{hit} = 72 bpm). It is important, and left to future work, to improve the detection of the IHR_i response.

The total number of SSVEP-based hand operations to perform was 32. Table 2 shows that subject s2 performed the predefined sequence without any error. Only after the sequence was completed did 1 FP detection occurr. This subject also achieved the highest classification accuracy during the SSVEP screening (table 1). The mean SSVEP-detection error rate of approximately 1 detection (out of 6.3 possible detections) every minute was satisfactory and enabled subjects to autonomously choose the timing (speed) to operate the SSVEP-based BCI.

During the setup of N_d we found that not all subjects were able to operate the 4-class BCI (table 2). This, however, could be expected considering the SSVEP classification accuracies achieved during the preliminary investigation (table 1). For these subjects we chose to reduce the number of classes by discarding non-reactive stimulation frequencies. To further increase the SSVEP classification accuracy, a more time consuming screening procedure (subject-specific stimulation frequencies) and/or more feedback training is necessary.

In this study we used very basic signal processing methods. Using more sophisticated methods for R-peak detection, SSVEP classification and artifact rejection might result in an improved performance. From the practical point of view, 1 bipolar EEG and 1 bipolar ECG channel are a minimum.

The results of this study suggest that transient HR changes, induced, for example, by brisk inspiration, can be used as a toggle switch. It could be shown that the heart rate response, in this work detected from the ECG, can be used as an information carrier and can contribute to the creation of BCI-based assistive devices. The next consequent and important step is to analyze whether mental simulation of action can induce a detectable HR response and be used as a switch in order to create a fully brain-actuated system.

Acknowledgments

This work was supported by the Lorenz–Böhler-Gesellschaft, the 'Steiermärkische Landesregierung', project GZ: A3-16 B 74-05/1, EU COST B27, EU Project PRESENCCIA IST-2006-27731 and the NeuroCenter Styria, Graz, Austria. The authors also would like to thank Otto Bock Healthcare, Austria, for providing the prosthetic hand.

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