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sBCI: Fast Detection of Steady-State Visual Evoked Potentials

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***Abstract*— Brain–computer interface (BCI) systems enable communication and control without movement. Although advanced signal processing methods are used in BCI research, the output of a BCI is still unreliable, and the information transfer rates are very low compared with conventional human interaction interfaces such as keyboard and mouse. Therefore, improvements in signal classification methods and the exploitation of the learning skills of the user are required to compensate the unreliability of the BCI system. This work analyzes the response time of the Bremen-BCI based on steady-state visual evoked potentials (SSVEP) previously tested on 27 subjects, and presents an enhanced method for faster detection of SSVEP responses. The aim is toward the development of a swift BCI (sBCI) that robustly detects the exact time point where the user starts modulating his brain signals.**

I. INTRODUCTION

Brain-computer interface (BCI) systems allow people to communicate and control external devices without using traditional motor output pathways [1]. Instead, direct measures of brain activity are translated into messages or commands by using a translation algorithm. Most non-invasive BCIs measure brain signals with electrodes mounted on the scalp via Electroencephalography (EEG). These signals have small signal-to-noise ratio, poor spatial resolution, and are very susceptible to external and internal interferences. Therefore, robust signal processing methods are needed to reliable detect and classify different brain patterns. Although advanced methods are used, the output of the BCI is still unreliable and the information transfer rates are very low compared with conventional interfaces.

The information throughput of the BCI depends mostly on the mental paradigm used to generate specific brain patterns [2]. Typically, BCIs that use selective attention strategies are faster than those using, for instance, modulation of sensorimotor rhythms [3]. In a selective attention task, the user focuses his attention on a particular stimulus. Rapidly oscillating stimuli produce steady-state visual evoked potentials (SSVEP) over occipital areas at corresponding frequencies [4]. If a user directs attention to one such stimulus, SSVEP activity can be used to infer user intent. Transient stimuli that the user attends produces a P300 potential [5].

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Online SSVEP-based BCI systems have exhibited performance up to 70 bit/min [6]. In the latest study with the Bremen-BCI system, information transfer rates up to 117 bit/min were achieved [7]. The Bremen-BCI provides high information transfer rates because of its robust signal processing methodology. For high information transfer rates, three parameters are closely related: The accuracy of the detection, the speed of the detection, and the number of frequencies that can be discriminated [2]. For example, shorter window lengths may speed up the detection time but also may reduce accuracy, or accuracy may be also affected with the number of frequencies that can be differentiated. The Bremen-BCI implements an approach that increases the signal-to-noise ratio in general, rather than improving one of these parameters individually.

This work briefly outlines the Bremen-BCI signal processing and presents an enhanced method to improve its detection algorithm by developing a faster SSVEP classification called the swift BCI (sBCI). The sBCI methodology aims to reliable detect the exact time point where users start modulating their brain signals. Future work includes the implementation of this algorithm online together with feedback structures that favor the learning process of the users.

II. METHODS

A. Database

Analyses were performed offline on data acquired from 27 subjects in a previous study (mean age was 23.59 ± 4.73 years, range was 18-35). Subjects' task was to spell five words with the Bremen-BCI system. The procedure to acquire the data was as follows. Each subject was first prepared for EEG recording. Next, a short familiarization run was performed in order to introduce the BCI system and the spelling device to the user. Three spelling tasks were identical for all subjects and were chosen by the experimenter (copy spelling), and two words were chosen by the subject (free spelling). The order in which these five phrases were spelled was randomized. Each trial ended automatically when the subject correctly spelled the desired word. The entire procedure took on average about 40 minutes per subject.

For each subject and each spelling task, a file containing EEG data recorded from six electrodes, output of the signal processing module, classification result, and window length used for signal processing was stored.

$$Data = \begin{cases} Y : electrode\ signals, \\ P : signal\ processing\ output, \\ R : result\ code, \\ L : current\ window\ length \end{cases} \quad (1)$$

The matrix Y of size $N_t \times N_y$ contains the sampled EEG signals measured as the voltage between a reference electrode and N_y electrodes for a time segment of N_t samples. Electrode signals for N_y electrodes can be represented in matrix form as:

$$Y = [y_1, \ldots, y_{N_y}]. \tag{2}$$

The matrix P is the signal processing output after applying the minimum energy combination algorithm [8] and normalizing SSVEP power estimations for all frequencies N_f into probabilities. The power distribution for N_f frequencies can be expressed as:

$$P = [p_1, \ldots, p_{N_f}]. \tag{3}$$

The size of P depends of the calculation interval used for computations. In this case, a calculation interval of approx. 100 ms (13 samples) and a sampling frequency of 128 Hz were used. The size of P is defined by $N_t/13 \times N_f$.

The vector R is the result of the classification process and can vary from 0 to 5. Result code 0 means that no frequency could be classified. For each command a corresponding result code is available (left $\hat{=}$ 1; right $\hat{=}$ 2; up $\hat{=}$ 3; down $\hat{=}$ 4; select $\hat{=}$ 5). The size of vector R is the total number of commands N_c. The vector L of size N_c contains the window length used for classification of each command.

B. Hardware and Software

The experiments were carried out at the Institute of Automation of the University of Bremen in a normal office room. Subjects were prepared for EEG recording with electrodes placed at positions P_Z, PO_3, PO_4, O_Z, O_9 and O_{10}. Data were referenced to the right ear lobe with a ground at site AF_z. EEG signals were digitized with 128 Hz sampling rate using a g.USBamp amplifier (Guger Technologies, Austria). An analog bandpass filter between 2 and 30 Hz, and a notch filter at 50 Hz were applied. The Bremen-BCI software system was used for all aspects of the SSVEP display, real-time data processing, feedback, and data storage. The visual stimulation was presented on a LCD screen (1680 $\times$ 1050 pixels) that presented a virtual keyboard and five white boxes, each one flickering at 7.5 Hz ("left"), 8.57 Hz ("right"), 10 Hz ("up"), 12 Hz ("down"), and 6.67 Hz ("select"). The size of each stimulus box was 150×150 pixels. Additional details of the display used in this study is available in [9].

C. Bremen-BCI Signal Processing

The signal processing module computes the power distribution of N_f frequencies every 100 ms using an adaptive time window length that can vary between 750 and 4000 ms. Incoming EEG signals in (2) are transformed into power signals in (3). Assuming a time window length T_s, and a matrix Y with N_t samples of electrode signals, sampled with a sampling frequency F_s, the power at stimulation frequency f is estimated as follows.

The first step of the signal processing module is to create a spatial filter that linearly combines the signals of all electrodes in a way that the background activity and noise are minimized [8]. The spatial filter creates several channels by making different combinations of the original electrode signals

$$S = WY, \tag{4}$$

where W is a $N_y \times N_s$ matrix containing the weights for each combination in its columns. N_s is the number of channels obtained after minimum energy combination.

The estimated signal power in the kth SSVEP harmonic frequency in channel signal s_l is given by

$$\hat{P}_{k,l} = \| X_k^T s_l \|^2, \tag{5}$$

where X contains the sine and cosine pairs with the SSVEP harmonic frequencies.

The average of the power over all N_s spatially filtered components and all N_h SSVEP harmonic frequencies for testing the presence of an SSVEP response is calculated by

$$T = \frac{1}{N_s N_h} \sum_{l=1}^{N_s} \sum_{k=1}^{N_h} \hat{P}_{k,l}. \tag{6}$$

In a BCI application with several stimuli, a test statistic T for each stimulation frequency is calculated. The test statistic for each frequency is then normalized into a probability:

$$p_i = \frac{T_i}{\sum_{j=1}^{j=N_f} T_i} \quad \text{with} \quad \sum_{i=1}^{i=N_f} p_i = 1. \tag{7}$$

The probability for each frequency is passed though a Softmax activation function to enhance SSVEP detection:

$$p'_i = \frac{e^{\alpha p_i}}{\sum_{j=1}^{j=N_f} e^{\alpha p_j}} \quad \text{with} \quad \sum_{i=1}^{i=N_f} p'_i = 1, \tag{8}$$

where α is set to 0.25. Each probability p_i is compared with an empirically determined threshold. If the highest probability exceeds the threshold, then the corresponding frequency is detected, and the control command associated with this frequency is executed.

Fig. 1 shows the output of the signal processing module of the Bremen-BCI for a subject that successfully spelled the word "BCI." Subject's task was to spell letters by navigating a cursor left, right, up, and down until the desired letter was reached. This letter could be then selected using the "select" command. The number of frequencies to detect was set to nine ($N_f = 9$), five stimulation frequencies ($6.66, 7.50, 8.57, 10.00, 12.00$ Hz) encoding five control commands and four additional frequencies ($7.08, 8.03, 9.28, 11.00$ Hz) for improving the robustness of the detection. The additional frequencies were calculated as the mean value between two target frequencies as proposed in [9]. Fig. 1(b) shows the power probability for each frequency and Fig. 1(c) the output of the classifier. For this spelling task, the user performed a total of nine commands. A command was executed when a signal exceeded the threshold of 35% (dotted line). After each classification, the signal processing module rejects 700 ms of EEG signals, because it is assumed that during this period the subject shifts gaze.

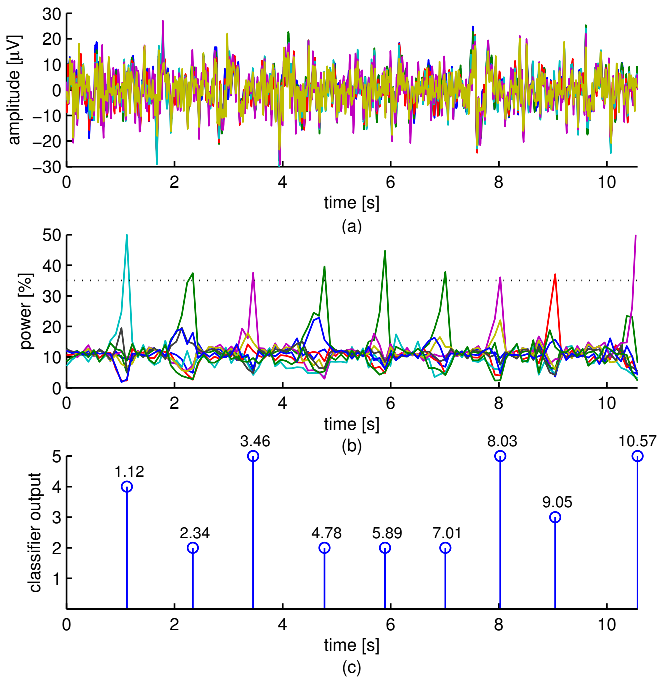

Fig. 1. SSVEP signal detection. (a) EEG signals acquired from the visual cortex ($N_y = 6$). (b) Each signal represents the normalized power calculated for a specific frequency ($Nf = 9$) over all spatially filtered components (Ns) and all SSVEP harmonic frequencies ($Nh = 2$). (c) Result of the classification ($1 \hat{=}$ left; $2 \hat{=}$ right; $3 \hat{=}$ up; $4 \hat{=}$ down; $5 \hat{=}$ select) and detection times.

D. *Fast BCI Signal Detection*

The classification of SSVEP signals in the Bremen-BCI is based on a classifier that detects a frequency when its probability exceeds a predefined threshold (35%), but information of the previous attempts of the user to execute the command is ignored. This problem can be addressed with an enhanced signal classification method. We called this new system the swift BCI or sBCI. The detection of SSVEP responses in the sBCI is based on signal energy calculation. The probabilities are integrated between the time when the signal exceeded a noise threshold and the time when the integration reached the new classification threshold. First, signals resulting from (8) are normalized by subtracting the offset produced by the probabilities when no frequency is detected. The offset is eliminated by subtracting $1/N_f$ from each signal p'_i. The offset subtraction step is necessary to avoid integrating noise signals in the next step that will unnecessary increase the integral.

Second, the energy of each signal is calculated by integrating the signal p'_i in a closed interval [a,b]. The lower limit *a* is defined as the time when the signal exceeded a noise threshold. It is assumed that below this threshold no visual stimulus is present and therefore, no classification is produced. The upper limit *b* is the time when the integration exceeds the classification threshold. In general, the energy of a signal p'_i is denoted by

$$e_i(t) = \int_a^b p_i(t)dt. \quad (9)$$

For a signal p'_i defined on the interval [a,b], the integral is calculated as:

$$e_i(t) = \sum_{i=1}^{n} p_i(t_i)\Delta t, \quad (10)$$

where Δt is defined by

$$\Delta t = t_i - t_{i-1} = \frac{b-a}{n}. \quad (11)$$

In other words, the classifier stores all previous attempts from the user when signals exceed a noise threshold until signal raises the classification threshold. When a frequency is detected, the integration process stops and its value is reset to zero until a signal reaches the noise threshold again.

III. RESULTS

The setup of the sBCI classifier was done on data recorded in a previous BCI study, in which subjects spelled five words with a mean accuracy of 93.87% (range 65.38 - 100%) and mean information transfer rate of 54.55 bit/min (range 5.87 - 117.39 bit/min). The parameters used to identify and classify SSVEP brain activity were calculated from offline data. In order to obtain good generalization, the classifier was validated on data from 27 subjects. The data was divided into training and test set. All parameters were determined on the training set (run with the word 'BCI") and final evaluation was performed on the test set (four remaining spelling tasks).

The parameters used to classify SSVEP patterns with the sBCI methodology are the noise threshold and the classification threshold. The sBCI signal detection is done in three steps: (a) power estimation, (b) offset subtraction and (c) integration. The noise threshold was selected at 10% and the classification threshold at 25%. Fig. 2 shows the results of the fast BCI classification algorithm for two subjects in comparison with the Bremen-BCI classification. With the sBCI method, six commands for subject S1 and seven for subject S7 could be earlier detected. In Fig. 2(b) top, the subject successfully executed first the "down" command at $1.52\,s$, and then executed the "right" command at $6.20\,s$ to reach the character "B." The user was instructed to change attention to the next target immediately after each classification result. Between 1.52 and $6.2\,s$, the subject was constantly focusing his attention to the light flickering with 8.57 Hz, but the system did not detect the frequency, the probability reached the threshold at $6.20\,s$. Next, the subject wanted to select character "B," he started focusing at the light flickering with 6.67 Hz. The selection occurred at $14.02\,s$. Again, several seconds passed until the system detected the "select" command. For selection of character "C" the execution of three "right" commands and one "select" was required. Finally, for the selection of "I", "up" and "select" were executed. The subject correctly spelled the word "BCI" with a completion time of $26.11\,s$, but in two opportunities the subject should concentrate longer on the flickering lights because the BCI did not detect the corresponding frequency. With the sBCI detection algorithm the classification times were considerably reduced, for example command 'left" was detected at $3.76\,s$ instead of $6.20\,s$, and the command

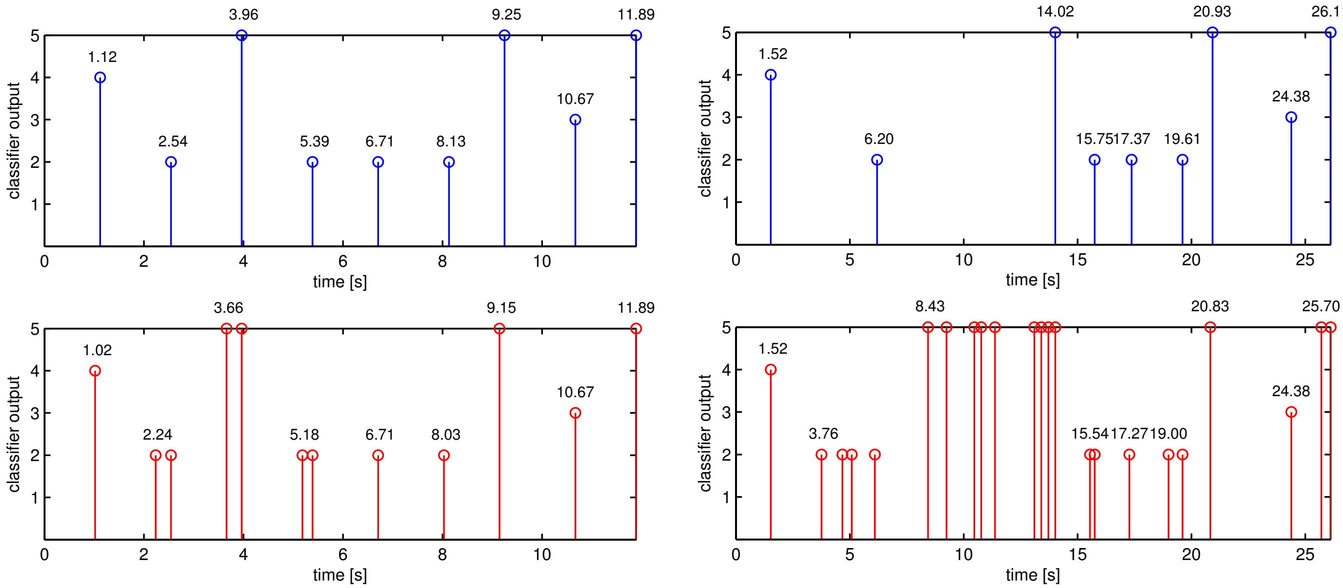

Fig. 2. Comparison of classification results for two selected subjects who used the Bremen-BCI to spell the word "BCI" (top) and the results obtained from offline analysis with the new sBCI method (bottom). In both cases, the sBCI provided a faster detection of commands. For subject S1 six commands and for subject S7 seven commands could be early detected.

"select" was detected at second 8.43 instead of 14.04. Multiple classifications for the same command are observed with the sBCI method because the signal processing was done with offline data. In an online BCI experiment, it is assumed that the subject will stop focusing attention on the stimulus directly after the classification, and therefore, no multiple classifications are expected. Thus, the speed of the BCI will be higher. The parameters used for evaluation were kept constant for all subjects. To obtain higher classification accuracies, it is recommended to calibrate system parameters for each subject. Online implementation of this algorithm will help to evaluate the behavior of the BCI system when fast detection is provided.

IV. CONCLUSIONS AND FUTURE WORK

The Bremen-BCI algorithm is simple to apply and gives reliable and robust results. Only few channels (6 channels) are necessary to achieve good results. The exact electrode placement is not critical, as the spatial filter is adaptively calculated for each data block. Most importantly, this BCI is also able to achieve high information transfer rates because of its adaptive window length [9]. Although these results are remarkable as no subject specific calibration was performed, the information transfer rates can be easily improved by using the sBCI methodology, which takes into account all previous attempts from the user to execute a command. As shown in the results section, all subjects could gain advantage of this method because SSVEP responses were detected faster and the first attempt to executed a command could produce a classification. Specially for subjects that do not show prominent SSVEPs, this method shortens the response time of the BCI. Some BCI applications demand considerably shorter response time as it is currently possible with present BCIs. As shown in this work, improvements in the signal processing can reduce the response time of the BCI by shortening the detection of specific brain patterns. However, we believe that also the exploitation of the learning skills of the user plays also an important role to compensate the slowness of the BCI. The user can learn for a specific application the times needed for the BCI to detect the desired command.

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