Proceedings of the
7th Graz Brain-Computer Interface Conference 2017 DOI: 10.3217/978-3-85125-533-1-85

COMPARISON OF SPEED, ACCURACY, AND USER FRIENDLINESS BETWEEN SSVEP-BASED BCI AND EYETRACKER

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ABSTRACT: This article intends to compare two rivaling technology tools that could reestablish communication for people with severe disabilities. One of the tested technologies, steady state visual evoked potentials (SSVEPs)-based Brain-Computer Interface (BCI), detects patterns in brain activity. Eye-tracking devices, on the other hand, measure the eye position, blinks, saccades, fixation paths, and other eye-specific parameters. Both methods can be used to interpret the users intent allowing control of spelling applications. Accuracy and speed of these two control methods are compared. A graphical user interface (GUI) with 30 targets (letters of the alphabet and special characters) was developed implementing each of the two technologies. Nine participants (two female) completed the phrase "RHINE WAAL UNIVERSITY" with both technologies. As expected, the achieved ITR with the eye-tracking device was significantly higher (91.8 bpm compared to 38.2 bpm for the SSVEP-based BCI). However, the eye tracking did not work for all of the participants, in this case the SSVEP-based interface can offer an alternative. The optimal interface needs to be customized individually.

INTRODUCTION

A brain-computer interface (BCI) can be seen as a specific type of Human-Cumputer Interaction (HCI) device. BCI can be defined as system that replaces, restores, enhances, supplements, or improves natural central nervous system output [1], or more general, as a device that communicates with other devices (or adjust the communication between them) via the brain signals [2]. The most common BCI approaches are the event-related desynchronization/synchronization (ERD/ERS) [27], steady state visually evoked potential (SSVEP) [28, 29, 16], and the P300 event-related potential (ERP) [3]. This article focuses on BCIs based on SSVEPs, neural responses which are evoked by repetitive visual stimuli (e. g. flickering boxes on a computer screen).

Though SSVEP-based BCIs have shown to be fast and reliable [4, 5], its dependency on eye gaze could exclude patients with lack of oculomotor control from using such systems and they therefore compete with other healthcare applications based on gaze direction. Another control method that also depends on gaze direction is eyetracking. Eye trackers are devices that compute the gaze direction; the calculated gaze coordinates can be used to classify objects the user is interested in. Typically, the eye movements are tracked by utilizing infrared technology and a high-resolution camera. Meanwhile commercial eye-tracking devices have become a valuable tool in augmentative communication [6].

Eye-tracking devices are generally considered more practical than SSVEP-based BCIs as they are faster and the required setup is much simpler; usually only the short calibration is necessary. However, some studies suggest that the performance gap between the two technologies might be smaller than expected. Kishore et al. compared the two methods using a head-mounted display (HMD) as a means of controlling gestures of a humanoid robot [7]. They found that both methods are appropriate for usage in immersive settings, but results for the eye tracker were surprisingly poor (two out of ten participants did not succeed in triggering gestures of a controlled robot using the eyetracker). It was stated though, that there were technological differences in this setup. Kosmyna and Tarpin-Bernard tested eye tracking in combination with different BCI paradigms in a gaming setup. Though they stated that the combination of eye tracking and SSVEP was slightly slower, it was more accurate than the pure EyeTracker [8].

One major obstacle with the eye tracking technology is the so called "Midas touch-problem" (see e. g. [9]). Usually the activation of a selected target object is based on dwell times; the user has to focus on a target object for an extended period. But the system cannot differentiate intentional from unintentional fixation, which can easily lead to false classifications. Another disadvantage is that any visual correction such as glasses or contact lenses can reflect the infrared (IR) light and thus make the readings inaccurate (optical eye trackers use the reflection of IR light for pupil recognition). Suefusa and Tanaka compared the eye-tracking with SSVEP when dealing with small targets [10]. They found that for short selection times the SSVEP-based BCI had higher information transfer rates (ITRs) then the eye-tracking interface for small size (square, 20 mm) targets. They suggested also that for small screen sizes (e. g. smartphone, tablets) BCI can be a better choice then eye-tracking.

The implementation of SSVEP-based BCIs as spelling interfaces has been a major research field in the BCI community. An important issue preventing a broader

 DOI: 10.3217/978-3-85125-533-1-85

use of BCIs is so-called BCI illiteracy (also synonymously called BCI deficiency), basically describing the fact that a BCI cannot detect the intentions of the user accurately [11]. That also takes into account the situations, if the classification accuracy cannot surpass a certain threshold of e. g. 70% [12]. The BCI literacy rate is defined reciprocally as the percentage of users who are able to achieve effective control over the BCI.

Meanwhile, a high number of targets can be implemented using SSVEP-based BCIs. Higher number of visual stimuli generally allow higher information transfer rates (ITRs). Hwang et al. developed a SSVEP-based BCI spelling system adopting a QWERTY-style LED keyboard [13]. Such multi target applications can also be implemented on computer screens using the frequency approximation method [14]. Up to 84 simultaneously flickering targets can be controlled utilizing this method [15].

This allows a direct comparison of the two technologies. In this respect, the reliability, speed and user friendliness of each system was investigated. Each technology was tested using a custom-made graphical user interface (GUI) utilizing 30 targets (letters of the alphabet and additional characters).

MATERIALS AND METHODS

Participants: Nine users (two female) with a mean age 23.8 years participated in the study, all students or employees of the Rhine-Waal University of Applied Sciences in Kleve. Participants were asked not to wear spectacles if their vision was sufficient to identify the individual targets, this was necessary because the extra IR reflection would lead to misreadings of the gaze coordinates. This study was conducted in accordance with the Declaration of Helsinki. All participants (healthy adult volunteers) gave written informed consent prior to the experiment. Information needed for the further analysis was stored anonymously, and cannot be traced back to the participants. No financial reward was granted for participation. This research was approved by the Ethical Review Board of the Medical Faculty of the University Duisburg-Essen (reference 16-6955-BO).

Hardware: Participants were seated in front of a LCD screen (BenQ XL2420T, resolution: 1920×1080 pixels, vertical refresh rate: 120 Hz) at a distance of about 60 cm. The used computer system operated on Microsoft Windows 7 Enterprise running on an Intel processor (Intel Core i7, 3.40 GHz).

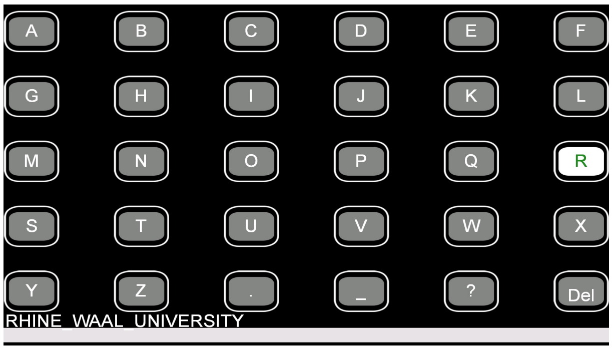

Figure 1: The Graphical User Interface. A participant was spelling the word “RHINE WAAL UNIVERSITY”.

For the BCI experiment, standard Ag/AgCl electrodes were used to acquire the signals from the surface of the scalp. The ground electrode was placed over AF_Z, the reference electrode over C_Z, and the eight signal electrodes were placed over $P_Z, PO_3, PO_4, O_1, O_2, O_Z, O_9$ and O_{10} in accordance with the international system of EEG electrode placement. Standard abrasive electrolytic electrode gel was applied between the electrodes and the scalp to bring impedances below $5\,k\Omega$. An EEG amplifier, g.USBamp (Guger Technologies, Graz, Austria), was utilized.
The sampling frequency was set to 128 Hz. During the EEG signal acquisition, an analogue band pass filter (between 2 and 30 Hz) and a notch filter (around 50 Hz) were applied directly in the amplifier.

Signal Acquisition: The minimum energy combination method (MEC) [16] was used for SSVEP signal classification. To detect the signal-to-noise ratio (SNR) of a specific frequency in the spatially filtered signals the SSVEP power estimations for all N_f frequencies were normalized into probabilities,

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

where $\hat{P}_i$ is the ith power estimation, $1 \leq i \leq N_f$.
Further, in order to increase the difference between probabilities, a Softmax function was aplied:

$$p'_i = \frac{e^{\alpha p_i}}{\sum_{j=1}^{j=N_f} e^{\alpha p_j}} \text{ with } \sum_{i=1}^{i=N_f} p'_i = 1\,, \tag{2}$$

with $\alpha = 0.25$.
All classifications were performed online on the basis of the hardware synchronization of the EEG amplifier (g.USBamp); the new EEG data were transferred to the PC in blocks of 13 samples (101.5625 ms with the sampling rate of 128 Hz). The classification was performed with a blockwise increasing time window (up to 160 blocks) [5, 16].
If the ith stimulation frequency had the highest probability p'_i and exceeded certain predefined thresholds β_i the corresponding target was classified. The thresholds

 DOI: 10.3217/978-3-85125-533-1-85

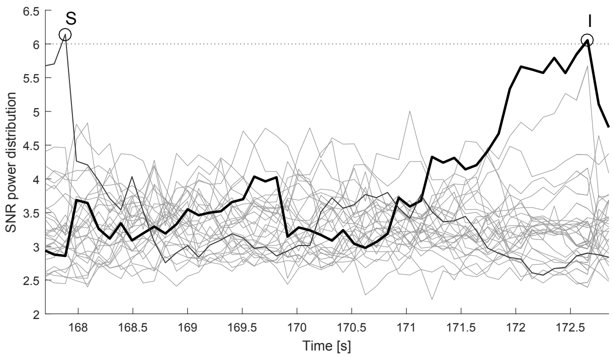

Figure 2: Thirty SNR values (equivalent to the number of flickering targets) for one participant (# 1) during spelling of the word "RHINE WAAL UNIVERSITY". The black line represents the SNR value of the frequency of the relevant box with the letter "I" and the threshold value (in this case 6) The SNR values representing the previous selection (letter S) is marked.

Figure 3: Path of the Eye-movement from the letter "S" to the letter "I" for participant # 1. The participant was spelling the word "RHINE WAAL UNIVERSITY". Before the selection of the letter "I" the eye tracker (TheEyeTribe) recorded several gaze positions across the path from "S" to "I", when the eye focused sufficiently long (2 seconds) on the desired box, the letter was selected.

of the SSVEP GUI were determined in a short calibration session where the user was asked to spell a short word of free choice. After each classification the classifier output was rejected for 914 ms (9 blocks). During this gaze shifting period, the targets did not flicker and the user could change her or his focus to another target unhindered (please also refer to [16] for more details). In this study the minimal classification time window was set to 2 seconds, same to the dwell time of the eye tracking interface.

This minimal time window is based on our previous studies that implemented this frequency approximation method [15, 17]. We have observed that a certain time (greater then the minimal 800 ms for SSVEP response [16]) is needed until the desired stimulation frequency can be detected in the EEG signal, in other words, the brain response to this duty cycle needs longer time windows.

In the frame-based stimulus approximation method a varying number of frames is used in each cycle [14, 15]. The stimulus signal at frequency f is generated by

$$\text{stim}(f, i) = \text{square}[2\pi f(i/\text{RefreshRate})], \qquad (3)$$

where $\text{square}(2\pi ft)$ generates a square wave with frequency f and i is the frame index.

E. g., the black/white reversing interval for the approximated frequency 17 Hz includes 17 cycles of varying length (three or four frames). By using the formula above, the one-second stimulus sequence of 17 Hz can be generated: (*4 4* 3 4 3 4 3 4 3 4 3 4 3 4 3 4 3 *4 4* 3 4 3 4 3 4 3 4 3 4 3 4 3). For the online spelling task with the SSVEP GUI approximated frequencies between 6.1 and 11.8 Hz (logarithmically distributed resolution, as suggested in our previous research [17]) were used to avoid overlapping in the 2-nd harmonics.

The Eye-Tracker (TheEyeTribe, Kopenhagen, Denmark) with the sizes $20 \times 1.9 \times 1.9$ cm, sampling rate 30 Hz, connected through USB 3.0 port to the PC was used for tracking the users gaze coordinates. For each participant a short (below 1 minute) eye tracking calibration run took place (9 point matrix) with the provided software.

Software:

The spelling interface displayed 30 buttons which were arranged into 5 rows (see Fig. 1). For the SSVEP system each box flickered, using the aforementioned frame-based stimulus approximation method. Any desired character could be selected in a single step. Each box was outlined by a frame which determined the maximum size a box could reach. The box sizes varied between 130×90 and 170×120 pixels, mirroring the current SNR power distribution of the corresponding frequency. For the eye-tracking system the box size mirrored the duration of the total gaze position frames over the box during the dwell time (longer gazing time on a box = bigger box). In order to further increase the user friendliness, every command classification was followed by an audio feedback with the name of the selected command or the letter spelled.

Experimental Setup: After signing the consent form, each participant was prepared for the EEG recording. Participants were asked to complete spelling tasks for both devices in random order. Initially users participated in a familiarization run, spelling the word "KLEVE" and a word of their own choice (e. g. their first name). Afterwards, they were instructed to spell the phrase "RHINE WAAL UNIVERSITY" (name of our University). The spelling phase ended automatically when the phrase was spelled correctly. In case a user was not able to execute a desired classification within a certain time frame, or if repeated false classifications occurred, the experiment was stopped manually. Spelling errors were corrected via the "delete" button. Information needed for the further analysis was stored anonymously during the experiment. After the test phase the participants completed a post-questionnaire, answering questions regarding the preferred spelling application. The entire session took on

 DOI: 10.3217/978-3-85125-533-1-85

Table 1: Results of the spelling performance. The phrase "RHINE WAAL UNIVERSITY" was spelled with the SSVEP, and Eye-Tracker interface, respectively. For each system one participant was not able to gain sufficient control. These two participants (3 and 9) were excluded from the calculation of the corresponding mean values.

	SSVEP				**Eye**			
Subject	Time [s]	Acc. [%]	ITR [bpm]	character/min	Time [s]	Acc. [%]	ITR [bpm]	character/min
1	184.133	81.82	35.91	10.75	62.867	100.00	98.35	20.04
2	188.906	78.38	36.47	11.75	64.796	100.00	95.42	19.45
3	N/A	N/A	N/A	N/A	107.111	86.21	59.43	16.24
4	91.711	100.00	67.41	13.74	56.063	100.00	110.28	22.47
5	431.641	73.33	17.36	6.26	60.125	100.00	102.83	20.96
6	200.180	83.87	32.39	9.29	70.890	95.65	86.39	19.47
7	114.359	100.00	54.06	11.02	61.242	100.00	100.96	20.57
8	156.914	95.65	39.03	8.79	75.563	95.65	81.05	18.26
9	276.859	86.21	22.99	6.28	N/A	N/A	N/A	N/A
Mean	205.588	87.41	38.20	9.74	69.832	97.19	91.84	20.18
SD	107.309	10.07	16.10	2.62	16.280	4.85	16.02	1.34

average about 35 minutes for each user. Participants had the opportunity to opt-out of the study at any time.

RESULTS

The overall BCI performance for both tested spelling applications is given in Table 1. Provided are the time T needed to complete the task, the command accuracy P and the commonly used information transfer rate (ITR) in bits/min:

$$B = \log_2 N + P \log_2 P + (1-P) \log_2 \left[\frac{1-P}{N-1}\right], \quad (4)$$

where B represents the number of bits per trial. The overall number of possible choices (N) was 30.
The accuracy P was calculated based on the number of correct command classifications divided by the total number of classified commands C_n. To obtain ITR in bits per minute, B is multiplied by the number of command classifications per minute. To obtain the average command classification time, the total time needed for the spelling task, T, was divided by C_n.

DISCUSSION

As can be seen in Table 1, BCI performance varied considerably between participants. While most participants performed better with the eye tracking GUI, not all were able to use it.
The average accuracy achieved with the SSVEP interface (87%) was significantly lower than the accuracy of the Eye-Tracking device (97%). A paired Student's t-test (with unpooled variances) revealed a statistically significant difference between the mean accuracies t(10) = 2.475, p¡0.05. Further, participants reached a mean ITR of 38.2 bpm with the SSVEP-based BCI and 91.8 bpm with the Eye-Tracking device, respectively. However, for each of the interfaces, one participant did not gain sufficient control.
Except for subject 9, all participants achieved better performance with the Eye-Tracking system.

Some users stated that the SSVEP interface was the more exhausting one. The comparably low accuracy also caused frustration for some participants. In addition to that, the time the user had to focus their gaze at a target was generally larger for the SSVEP GUI. The average command classification time (including the gaze shifting period) was 7.3 seconds for the SSVEP GUI, which is considerably longer than the mean classification times for the eye tracking system (on average 5.9 seconds). The importance of the of appropriate time window length has already been discussed e. g. in [18].

The obtained performance with the SSVEP GUI is quite promising; a mean ITR of 29.82 bpm was achieved. These results indicate the potential use of noninvasive SSVEP-based BCIs as a standalone high-speed communication tool. Though multitarget BCIs usually allow higher speed, slightly worse BCI accuracies have been previously reported with a higher number of stimuli [15]. The literacy rate is generally higher with BCIs implementing a low number of visual stimuli; some larger BCI studies with only four targets reported that even all users were able to gain control over the application [4, 5, 19]. Higher classification accuracies can be achieved with fewer targets [15]. Low target SSVEP-based BCI are therefore more suitable for hybrid systems, which combine input signals of different brain patterns, or biosignals such as eye gaze (see e. g. [20, 21, 22, 23, 24]).

Reliability of such systems could be improved further e. g. through user specific parameter setup [5].

While speed attracts much attention in development of BCI application, high accuracies are the priority for control applications and also tend to provide the highest literacy rate. This is especially relevant as demographic factors influence BCI performance, e. g. elderly people are slightly poorer BCI performers [25]. Eye tracking devices, on the other hand, may be affected by the ethnicity

DOI: 10.3217/978-3-85125-533-1-85

(e. g. asian origin) or physiology (e. g. ptosis of the eyelid) factors of the participant [26].
Further tests with brain-injured patients are desirable, as results might differ from findings of this study. In future our focus lies on further development of low target SSVEP-based BCIs and data fusion with eye tracking devices.

CONCLUSION

The presented study compares performance of an SSVEP-based BCI with an Eye-Tracking device. These two communication technologies were tested with nine healthy participants in order to explore the speed and accuracy of each system.
Though all participants achieved reliable control over at least one of the tested systems; both the SSVEP-BCI system as well as the system based on Eye-Tracking could not interprete the user intend accurately in all cases. The comparison of mean values for literate participants shows that ITR as well as classification accuracy was significantly higher for the Eye-Tracking device. The results demonstrate, however, that each of the devices has its advantages and disadvantages, and should be chosen for each user individually.

ACKNOWLEDGEMENT

This research was supported by the European Fund for Regional Development under Grant GE-1-1-047. The authors thank the participants and student assistants: Aya Rezeika, Frederike Oetker, Linh-Nga Tran, Mariya Kamenshchikova, Mihaly Benda for their help during the study.

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