Spelling with Steady-State Visual Evoked Potentials

Ola Friman, Thorsten Lüth, Ivan Volosyak and Axel Gräser

Abstract— **In this work, the real-time performance of a novel method for detecting Steady-State Visual Evoked Potentials (SSVEP) is evaluated in a brain-computer interface (BCI) spelling task. At the core of this method is a spatial filtering algorithm for extracting SSVEP responses, which in previous off-line studies has shown significantly improved classification performance. The on-line performance is investigated by letting a group of 11 healthy subjects spell the word 'BRAINCOMPUTERINTERFACE'. In this task, an average information transfer rate of 29 bits/minute was obtained, and the probability of correctly classifying the user's intention was estimated to 97.5%. In addition, two different letter layouts and selection schemes tailored for SSVEP BCI's are compared.**

I. INTRODUCTION

A main goal in brain-computer interfacing is to provide means of communication for severely disabled people. To date, the perhaps most successful BCI applications are spelling devices which allow users to write text messages by voluntarily controlling their brain signal patterns. The first BCI spelling application was based on the P300 signal pattern [1]. A number of other brain signals have also been successfully utilized for spelling, e.g., Slow Cortical Potentials [2] and ERD/ERS [3]. The BCI presented in this work is based on Steady-State Visual Evoked Potentials (SSVEP), which is a brain response evoked mainly in the visual and parietal cortexes as a response to flickering visual stimuli [4]. The SSVEP phenomenon has gained interest in the BCI community because it provides advantages in terms of speed and robustness. These advantages can be attributed to the fact that SSVEP responses are strong and robust signals which can be well modeled and detected. An SSVEP-based BCI relies on external visual input in form of an array of light sources, where each light source is flickering with a distinct frequency [5], [6]. By analyzing the frequency content in recorded electroencephalography (EEG) signals, the light source on which the user is focussing can be inferred, and an associated command is subsequently issued. Herein lies the main limitation of an SSVEP-based BCI; the subject controlling the BCI must be able to move the eyes in order to focus on one of several light sources. This restriction excludes users who do not have this ability and who would benefit the most from the BCI technology. Clearly, competing technologies can be used when the subject is able to move the eyes, e.g., a communication device based on eye-tracking. To assess the relative merits of different technologies their respective state-of-the-art performances should be compared, and this work can be seen as a step towards such a goal. Moreover, it may be the case that hybrid methods will turn out to work very well, e.g., a combination of SSVEP and eye-tracking.

There are two main goals in this work. First, in [7] a novel spatial filtering algorithm was presented, with which it is possible to detect SSVEP responses more accurately compared to previous methods. One goal is to investigate the information transfer rate that can be obtained with this improved detection algorithm in a real BCI application. The second goal is to investigate spelling applications tailored for SSVEP-based BCI's. Two different spelling layouts and letter selection methods are evaluated. The outline of the following sections are as follows: First, the implementation of the above-mentioned SSVEP detection algorithm is described. Next, the two letter selection methods are presented. Finally, the information transfer rates and the letter selection methods are investigated in a group of 11 healthy subjects.

II. REAL-TIME SSVEP DETECTION

The SSVEP response to visual stimulation with a light source flickering with a frequency f_0 is well modeled as a superposition of a number of sinusoids with frequencies f_0, $2f_0$, $3f_0$,…, i.e., the fundamental stimulation frequency and its harmonics. In [7], a novel spatial filter which extracts the SSVEP response from multiple electrodes placed over the visual and parietal cortexes is presented. This procedure is briefly explained below. First, let $\mathbf{Y}$ be a matrix where each column contains the signal from one electrode location. Let $\mathbf{X}_f = [\sin(2\pi f t)\ \cos(2\pi f t)]$ be a model matrix containing a sine and a cosine of frequency f and let $\mathbf{X} = [\mathbf{X}_{f_0}\, \mathbf{X}_{2f_0}\, \mathbf{X}_{3f_0}]$ be a matrix where the columns span the signal subspace in which the SSVEP response is assumed to reside. The goal is to find a spatial filter vector $\mathbf{w}$ that cancels as much of the interference and nuisance signals in $\mathbf{Y}$ as possible. To this end, a modified signal matrix $\tilde{\mathbf{Y}} = (\mathbf{I} - \mathbf{X}\left(\mathbf{X}^T\mathbf{X}\right)^{-1}\mathbf{X}^T)\mathbf{Y}$, where the energy in the SSVEP frequencies has been removed, is first calculated. The filter vector $\mathbf{w}$ is subsequently found as the eigenvector belonging to the smallest eigenvalue of the matrix $\tilde{\mathbf{Y}}^T\tilde{\mathbf{Y}}$. A spatially filtered signal is finally calculated as $\mathbf{Y}\mathbf{w}$, where it is important to emphasize that the filter is applied to the original signals in $\mathbf{Y}$. The SSVEP response strength is quantified by calculating a SSVEP-response-to-noise ratio (SNR) for the filtered signal, i.e., the SSVEP response strength is contrasted with an estimate of the noise power in the same frequencies. The noise power is estimated by means of an autoregressive $AR(5)$ model fitted to the spatially filtered

---

This research project has been supported by a Marie Curie Transfer of Knowledge Fellowship of the European Communitys Sixth Framework Programme under contract number MTKD-CT-2004-014211.

The authors are with the Institute of Automation, University of Bremen, Otto-Hahn Allee 1, 28359 Bremen, Germany. Corresponding author is O. Friman `ofriman@iat.uni-bremen.de`

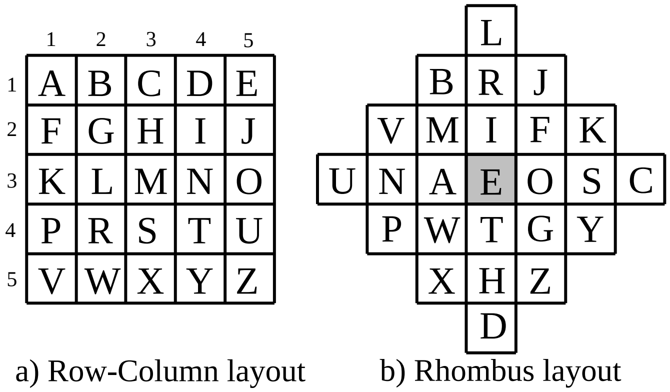

Fig. 1. **a)** The Row-Column layout, where letters are chosen by first selecting the row containing the desired letter and then the column. **b)** The Rhombus layout, in which a cursor is navigated right, left, up and down to reach the desired letter. Once the letter has been chosen, the cursor jumps back to the center position.

signal. When applied in an off-line analysis of recorded SSVEP data, this algorithm gave the best performance in a comparison between six different detection methods [7]. Note that the algorithm does not rely on any calibration or training data. For the current work, to obtain real-time performance, a BCI system was implemented in C++ where the detection algorithm described above is included as a class. This code is available upon request.

III. SPELLING LAYOUTS

Depending on the number of distinct brain patterns that can be distinguished, different strategies for selecting letters in a spelling application are required. When only two different patterns can be discriminated, a tree layout may be suitable [8], e.g., a letter is selected by recursively partitioning the alphabet until only the desired letter remains. Another layout suitable for binary commands is the recently proposed Hex-o-Spell [9], which also employs a recursive partitioning scheme. In spelling applications designed for P300 BCI's, the alphabet is typically arranged in a 2-dimensional grid and a letter is selected by first choosing the row and then the column of this letter [1]. With a BCI based on the SSVEP response, a relatively large number of commands can be distinguished. In the current work, 5 different commands are used, requiring five different light sources that flicker with different frequencies. In Fig. 1, two different spelling layouts designed to be controlled with these 5 commands are shown. The layouts contain 25 of the 26 letters in the English alphabet (the letter Q is excluded). It should be stressed that the two presented layouts are used for evaluation purposes only and that more symbols are required in a final layout. This can be achieved by extending the layouts and/or introducing more SSVEP frequencies that encode more commands. For example, a delete function could be implemented using a sixth light source. The layout in Fig. 1a is here referred to as the Row-Column layout, and it is similar to the design commonly used in P300 spelling programs [1]. Letters are chosen by first selecting the row and then the column of the desired letter. That is, the selection of a letter requires two decisions. In the alternative layout in Fig. 1b, which is referred to as the Rhombus layout, letters are instead selected by navigating the cursor right, left, up and down until the desired letter is reached. This letter is then selected using the fifth SSVEP frequency. Once a letter has been selected, the cursor starts over at the center position. That is, except for the letter E, two or more commands must be executed to select a letter and this layout is therefore expected to be slower than the Row-Column layout. On the other hand, the Rhombus layout is more forgiving against error-classifications, for example, an accidental "up"-command can easily be corrected by the user. The Rhombus layout was constructed with the assumption that it is easier to keep a constant visual attention on one flickering light source for an extended time to produce repeated selections of the same command than to switch attention between the light sources. To ensure that common letters are reached with a minimum of effort, the letters were ordered with respect to both their occurrences in the English language as well as to the number of attention-switches between light sources required. For example, in the Rhombus layout in Fig. 1b, two commands are required to reach the letters 'M' (*left-up*) and 'N' (*left-left*). Since the letter 'N' is about twice as common in the English language as the letter 'M' (relative frequencies about 6% and 3% respectively), the letter 'N' is in the layout reached with the *left-left* command sequence which is assumed faster to execute than the *left-up* sequence. The letters in Fig. 1b were ordered manually with the above considerations in mind and it should therefore be seen as a good ordering rather than an optimal ordering. More importantly, these considerations lead to the rhombus shape instead of a square shape of the layout, because more letters can be reached without any attention switches at all in the rhombus shape than in a square layout. The spelling layouts were also implemented in C++ and they receive commands from the analysis software via a TCP/IP connection.

IV. SUBJECTS AND DATA ACQUISITION

11 healthy subjects (1 female and 10 male) in the ages 21-58 years (mean age 30.1 years) were recruited for the current work. Only 1 of the subjects (Subject #1) had prior experience of the BCI and the spelling task. 6 gold electrodes were placed over the visual and parietal cortex (2 electrodes at positions O_Z, P_Z according to the international 10-20 system and 4 electrodes 2.5 cm above and under the positions O_1 and O_2 respectively). These electrodes were referenced to a ground electrode placed at position F_Z. The measured signals were amplified using a g.BSamp amplifier from g.tec and filtered through analog high-pass and low-pass filters with cut-off frequencies of 0.5 Hz and 32 Hz respectively. Electrode impedances were at all times kept below 5 $k\Omega$. The amplified signals were digitized using a National Instruments acquisition card DAQ6024E at a sampling rate of 128 Hz and further processed on a regular laptop computer with a 1.73 GHz Pentium M processor. Both

the SSVEP processing application described in Section II and the spelling programs described in Section III ran on the same computer. For visual stimulation a custom made array with 5 red light emitting diodes (LED's) was used. These LED's were flickering with the five frequencies 13, 14, 15, 16 and 17 Hz respectively. These frequencies encode the five commands needed to operate the spelling layouts, and they were chosen because previous studies have shown that the strongest SSVEP responses are evoked in this range [10]. The harmonics of stimulation frequencies larger than 32 Hz (cut-off of the low-pass filter) were not used for the SSVEP detection. Each LED covered an area of about 2×4 cm. The subjects were placed in a comfortable chair with about 0.5 m viewing distance to the LED's and the screen of the laptop. During the acquisition the room was dimmed.

	Row-Column layout			**Rhombus layout**		
	Minimum 44 commands			Minimum 58 commands		
	Time	Errors	Bits/min	Time	Errors	Bits/min
Subject #1	2:40	0	38	3:01	0	45
Subject #2	3:02	2	34	3:32	0	38
Subject #3	2:27	1	42	5:11	0	26
Subject #4	3:20	0	31	4:25	0	30
Subject #5	3:56	1	26	4:29	1	30
Subject #6	3:52	0	26	4:40	0	29
Subject #7	3:53	1	26	4:40	2	29
Subject #8	4:34	1	22	5:14	2	26
Subject #9	5:16	1	19	4:34	0	29
Average	**3:40**		**29.3**	**4:25**		**31.3**
Subject #10	-	-	-	9:06	6	15
Subject #11	-	-	-	11:13	8	12
Average	-		-	**5:28**		**28.1**

TABLE I

EXPERIMENTAL RESULTS

V. METHOD

The 11 subjects were given the task to write the word 'BRAINCOMPUTERINTERFACE' (22 letters) with the two spelling layouts presented in Section III. In the Row-Column layout, 2 commands are required to select a letter, and therefore a total of 44 commands are required to write this word. In the Rhombus layout it takes a minimum of 58 commands to write the task word. The SSVEP detection algorithm was set to take 2 seconds of EEG data into account for detecting SSVEP responses in the recorded signals, as this length has been observed to give a good speed vs. detection accuracy trade-off. Likewise, an idling period of 2 seconds was used after a classification to acquire fresh data for the next classification. An SNR threshold was used for detecting significant SSVEP responses. This threshold was initially set to a default value of 4, but for some subjects who had very strong SSVEP responses the threshold was raised to 6 to further reduce the probability of false positive classifications. Via Monte Carlo simulations it can be shown that the probabilities that the SNR of *any* of the five stimulation frequencies exceeds 4 and 6 by chance are 0.05 and 0.002 respectively.

Since the users were new to the spelling task and the spelling layouts, they were asked to play around with the system and each spelling layout for a few minutes, e.g., by writing their names, before the actual spelling task. Based on the strength of SSVEP responses (which were plotted on-line) generated in this initial testing, the classification threshold was adjusted for strong performing subjects as mentioned above. All subjects felt ready for the actual task within 5 minutes. The subjects were then asked to first write the task word using the Rhombus layout and then with the Row-Column layout. To evaluate the performance, the time required to complete the spelling task was measured and the number of errors made was recorded. An error was counted when the BCI made a classification that did not agree with the user's intention, e.g., a cursor-movement to the left when the intention was an up-movement. The subjects were asked to report such errors to the person monitoring the experiment. If an error resulted in a false letter being written the subject was instructed to rewrite the desired letter so that all letters in the task word were written.

VI. RESULTS

The resulting times, errors and information transfer rates ([11]) for the 11 subjects are reported in Table I. The subjects are sorted according to their performance, i.e., Subject #1 had the highest average bit-rate and Subject #11 the lowest. Moreover, Subject #10 and Subject #11 were only able to complete the task within reasonable time ($<$ 15 minutes) using the Rhombus layout and not with the Row-Column layout. The reason for this is that these two subjects had weak SSVEP responses and that they consequently had problems producing SNR's exceeding the threshold. As briefly touched upon previously, false-positive errors cause less harm in the Rhombus layout since in most cases an error only means that the cursor moves one step in the wrong direction and only rarely is the *select* command triggered by chance. Hence, even if it took some time, these two subjects were able to write the entire task word using the Rhombus layout with very few actual spelling errors. In the Row-Column layout all commands are implicitly select-commands, and Subject #10 and Subject #11 therefore experienced problems with this layout.

Studying the 9 remaining subjects who wrote the task word with both spelling layouts, the average times reveal that the Row-Column layout is faster than the Rhombus layout (paired t-test $p = 0.036$). The main reason is that fewer commands must be executed to complete the spelling task with the Row-Column layout. This layout was also preferred by most of the subjects. Note, however, that the bit-rate is higher for the Rhombus layout and the average time to generate a correct command using the Row-Column layout is 5 seconds and 4.6 seconds for the Rhombus layout (paired t-test $p = 0.29$). From the raw numbers it is not possible to tell if this is due to a fatigue effect (the Rhombus layout was always used before the Row-Column layout), due to the design of the Rhombus layout which was made so that the sequence of commands is easy and fast to execute, or due to chance. However, since the experiments were quite short and included pauses, one may guess that the difference is not due to fatigue.

VII. DISCUSSION

There are two main aims in this work. The first is to evaluate a novel SSVEP detection algorithm in a real-time BCI application. The second aim is to present spelling applications tailored for SSVEP-based BCI's and to evaluate their merits. The speed obtained using the novel detection algorithm ranges between 10 and 45 bits/minute, with an average of about 30 bits/minute. It is difficult to do meaningful comparisons with previously reported speeds (due to, for example, different number of LED's and different tasks), but the speed must be considered as high. The high classification accuracy of about 97.5 % should also be emphasized, as well as that very little subject-specific adaptation of the BCI is required (only the detection threshold was adjusted in this work). Thus, the BCI can be said to follow the plug-and-play principle. This does, however, not mean that training and tuning would not improve the performance further. As an example, it was observed that several of the subjects had problems and spent lots of time trying to produce an SSVEP signal with the lowest 13 Hz stimulation frequency, whereas the higher frequencies did not pose any problems at all. These subjects would have completed the spelling task considerable faster had the stimulation frequencies been shifted to the interval 14 - 18 Hz instead. Moreover, a majority of the subjects spontaneously commented that they would be able to complete the spelling task much faster with some practise because they would then know the locations of the letters in the layouts, and there would be no need to switch the attention between the LED's and the computer screen. In the literature it is commonplace to report the number of characters that can be written per minute with the BCI system. This is clearly a very relevant quantity for the end-user. In this work, Subject #3 was able to write 9 letters per minute with the Row-Column layout. As a comparison, in [12] a speed of 7.8 characters per minute and a 80% classification accuracy are reported with a P300-based BCI and a similar row-column layout. It should be mentioned that this latter layout consisted of 6 rows and columns, whereas the Row-Column layout in this work consists of only 5 rows and columns. However, extending the current layout with one extra row and column, and an extra LED, would not pose any problems for the high-performance subjects in this study. As was discussed in the Introduction, SSVEP-based BCI's can be expected to be faster than, for example, P300-based BCI's. On the other hand, as also already discussed, P300-based BCI's are potentially useful for a larger group of people than SSVEP-based BCI's. In the comparison between the Row-Column layout and the Rhombus layout, the Row-Column layout was found to be significantly faster, the main reason being that fewer commands must be executed to select a letter in the Row-Column layout. However, the Rhombus layout was found better for subjects with weaker SSVEP signals. Thus, the Rhombus layout may be useful in combination with a P300 BCI, because the P300 response is in general weaker and more difficult to detect than the SSVEP response. Finally, to maximize writing speed, a final spelling application should of course be supported by stronger language models that can make informed guesses of the next letter as well as the entire next word.

VIII. CONCLUSIONS

A real-time implementation of a novel SSVEP detection algorithm has been evaluated in a brain-computer interface spelling application. Information transfer rates of up to 45 bits/minute using 5 different commands were obtained. Two different spelling layouts designed for SSVEP-based BCI's were also evaluated, and it was found that the Row-Column layout was faster than the Rhombus layout, especially for strong performing subjects. For lower-performing subjects, the Rhombus layout may be more suitable since it is more forgiving against false-positive error classifications.

REFERENCES

[1] L. Farwell and E. Donchin, “Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials,” *Electroencephalogr Clin Neurophysiol*, vol. 70, no. 6, pp. 510–523, 1988.

[2] A. Kübler, B. Kotchoubey, T. Hinterberger, N. Ghanayim, J. Perelmouter, M. Schauer, C. Fritsch, E. Taub, and N. Birbaumer, “The thought translation device: a neurophysiological approach to communication in total motor paralysis,” *Experimental Brain Research*, vol. 124, no. 2, pp. 223–232, 1999.

[3] B. Obermaier, G. Mller, and G. Pfurtscheller, “”Virtual keyboard” controlled by spontaneous EEG activity,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 11, no. 4, pp. 422–426, 2003.

[4] D. Regan, *Human Brain Electrophysiology: Evoked Potentials and Evoked Magnetic Fields in Science and Medicine*. Elsevier, New York, 1989.

[5] M. Middendorf, G. McMillan, G. Calhoun, and K. Jones, “Brain-computer interfaces based on the steady-state visual-evoked response,” *IEEE Transactions on Rehabilitation Engineering*, vol. 8, no. 2, pp. 211–214, 2000.

[6] M. Cheng, X. Gao, S. Gao, and D. Xu, “Design and implementation of a brain-computer interface with high transfer rates,” *IEEE Transactions on Biomedical Engineering*, vol. 49, no. 10, pp. 1181–1185, 2002.

[7] O. Friman, I. Volosyak, and A. Gräser, “Multiple channel detection of steady-state visual evoked potentials for brain-computer interfaces,” *IEEE Transaction on Biomedical Engineering*, 2007, in press, scheduled for March number. Preprint available for download at IEEEXplore website.

[8] J. Perelmouter, B. Kotchoubey, A. Kübler, and N. Birbaumer, “Language support program for thought-translation devices,” *Automedica*, vol. 18, pp. 67–84, 1999.

[9] B. Blankertz, G. Dornhege, M. Krauledat, M. Schrder, J. Williamson, R. Murray-Smith, and K.-R. Mller, “The Berlin brain-computer interface presents the novel mental typewriter Hex-o-Spell,” in *Proceedings of the 3rd International Brain-Computer Interface Workshop and Training Course*. Verlag der Technischen Universität Graz, 2006.

[10] C. Herrmann, “Human EEG responses to 1-100 Hz flicker: resonance phenomena in visual cortex and their potential correlation to cognitive phenomena,” *Experimental Brain Research*, vol. 137, no. 3-4, pp. 346–353, 2001.

[11] J. Wolpaw, N. Birbaumer, W. Heetderks, D. McFarland, P. Peckham, G. Schalk, E. Donchin, L. Quatrano, C. Robinson, and T. Vaughan, “Brain-computer interface technology: a review of the first international meeting,” *IEEE Trans Rehabil Eng*, vol. 8, no. 2, pp. 164–173, 2000.

[12] E. Donchin, K. Spencer, and R. Wijesinghe, “The mental prosthesis: assessing the speed of a P300-based brain-computer interface,” *IEEE Transactions on Rehabilitation Engineering*, vol. 8, no. 2, pp. 174–179, 2000.