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Age-related differences in SSVEP-based BCI performance

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ABSTRACT

Brain–Computer Interface (BCI) systems analyze brain signals to generate control commands for computer applications or external devices. Utilized as alternative communication channel, BCIs have the potential to assist people with severe motor disabilities to interact with their environment and to participate in daily life activities. Handicapped people from all age groups could benefit from such BCI technologies. Although some papers have previously reported slightly worse BCI performance by older subjects, in many studies BCI systems were tested with young subjects only.

In the presented paper age-associated differences in BCI performance were investigated. We compared accuracy and speed of a steady-state visual evoked potential (SSVEP)-based BCI spelling application controlled by participants of two different equally sized age groups. Twenty subjects (eleven female and nine male) participated in this study; each age group consisted of ten subjects, ranging from 19 to 27 years and from 64 to 76 years. Our results confirm that elderly people may have a deteriorated information transfer rate (ITR). The mean (SD) ITR of the young age group was 27.36 (6.50) bit/min while the elderly people achieved a significantly lower ITR of 16.10 (5.90) bit/min. The average time window length associated with the signal classification was usually larger for the participants of advanced age. These findings show that the subject age must be taken into account during the development of SSVEP-based applications.

1. Introduction

A Brain–Computer Interface (BCI) is a technical system that acquires and analyzes brain activity patterns in real time to translate them into control commands for computers or external devices [1,2]. BCIs have received much attention in recent years and there has been consistent growth in the number of papers mentioning the term BCI since 2001 [3]. There are many different control paradigms for BCIs, e.g. the event-related desynchronization/synchronization (ERD/ERS)-paradigm [4], and the P300 event-related potential (ERP)-paradigm [5,6]. In the presented paper we use so-called steady-state visual evoked potential (SSVEP)-based BCIs, which represent another standard BCI paradigm (see e.g. [7]). Steady-state visual evoked potentials are the continuous brain responses elicited at the occipital and parietal cortical areas under visual stimulation (e.g. flickering box on a computer monitor) with a specific constant frequency.

When focusing at a target of a set consisting of several constantly flickering visual stimuli, normal brain signals are modulated with the corresponding frequency. These are then non-invasively recorded by an electroencephalogram (EEG) and identified in real time. BCI applications can assist people paralyzed by disorders such as cerebral palsy, spinal cord injury, brain stem stroke, amyotrophic lateral sclerosis (ALS), or muscular dystrophies to participate in daily life activities [8].

Those disorders can be found among all age groups. Also, the effects of aging alone present physical limitations that all-too-often prevent older people from interacting with their environment. Although the specific needs of all different age groups should be considered during BCI development, the majority of BCI systems were tested with younger subjects. However, increasing effort has been made to conduct studies with the target population. Several BCI systems have been tested in lifelike scenarios [9–11].

Some papers have previously reported slightly worse BCI performance by subjects of advanced age. E.g., in a 12 participant study about latency and distribution of P300, Dias et al. found that elderly subjects (>51 years) show smaller P300 amplitudes than younger ones [12]. Grosse-Wentrup and Schölkopf reviewed performance variations in BCIs based on the sensorimotor-rhythm (SMR) and stated that a negative correlation between age and BCI performance is conceivable [13]. Furthermore, Macpherson et al. investigated age-associated changes in SSVEP amplitude and la-

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tency with memory performance [14]. They found that older adults demonstrated reduced neural activity during lower task demands, whereas with greater task demands, their neural activity was increased. Research on accuracy in SSVEP-based BCIs frequently reported variations in performance between users. Ehlers et al. reported age group distinctions concerning accuracy rates of a performance with a SSVEP-based spelling application [15], but only children and young adults between 6 and 33 where tested in this study. The young adults obtained higher accuracy rates compared to children. Hsu et al. studied the amplitude-frequency characteristics of frontal and occipital SSVEPs in young, elderly and ALS patients [16]. They found that the amplitudes of occipital SSVEPs in the young group (mean age 24.25 years) were significantly larger than the amplitudes of the elderly group (mean age 54.13 years). Research papers on so-called BCI demographics in SSVEP BCIs also reported age-related performance differences. Allison et al. analyzed the spelling performance with a SSVEP-based spelling application. It was observed that younger subjects were less annoyed by the flickering and tended to attain a higher information transfer rate (ITR) [17]. However, in this relatively large study only few subjects were over 50 years old. In another subsequent demographics study, subjects between 18 and 55 years were tested, but neither a statistically significant effect of age, gender, nor their interaction were observed [18].

In order to explore the age-related BCI performance differences further, we tested two equally sized groups of different age ranges with a SSVEP-spelling application. The use of BCI as a spelling interface has been one of the main focuses in BCI studies. A strong correlation between BCI accuracy and the length of the time window dedicated to the SSVEP classification during EEG analysis has been observed [19,20]. Generally speaking, a short time window results in classification errors, and a long time window slows down the BCI performance. In many practical experiments with subjects it was found that some users (especially elderly subjects) need to gaze at the stimulation target for a relatively long period of time, hence a long time window seems to be necessary to achieve control of the BCI system [18].

High classification accuracies are an essential goal in BCI research. A key factor in ensuring effective control is the arrangement and number of the visual stimuli. Especially for elderly people, the readability and simplicity of the graphical user interface (GUI) are crucial. Moreover, the amount of subjects that are able to gain control over a SSVEP-based BCI as well as the performance accuracies are comparably larger if only four simultaneously displayed stimuli are used [18,21]. Because of this, we used a rather small number of simultaneously displayed targets. As opposed to five classes as in [15,17,22], only four simultaneously flickering boxes containing all letters of the English alphabet were used.

In the presented study age related performance differences in SSVEP-based BCIs are analyzed and discussed. Through limiting the number of simultaneously displayed targets and extending classification time windows, we aim to close the performance gap between older and younger test subjects.

2. Methods and materials

2.1. Participants

Two groups of ten healthy volunteer subjects each participated in the study. The group of younger subjects (*groupA*) had a mean (SD) age of 22.4 (2.92) years, ranging from 19 to 27. All subjects from this group were students or employees of the Rhine-Waal University of Applied Sciences and had no previous experience with BCI systems. Four subjects of this group were female. The other group (*groupB*) consisted of three male and seven female volunteer subjects, with a mean (SD) age of 67.3 (5.66) years, ranging from 54 to 76. None of the twenty subjects had ever used a BCI. All subjects had normal or corrected-to-normal vision. Spectacles were worn if needed.

All participants gave written informed consent in accordance with the Declaration of Helsinki before taking part in the experiment. Information needed for the analysis of the test was stored anonymously during the experiment. The entire session lasted on average approximately 60 minutes for each subject. Subjects had the opportunity to withdraw from participation at any time.

The EEG recordings were conducted in a typical laboratory setting with low background noise and luminance. All persons who volunteered to participate in the study became research subjects after reading a subject information sheet and signing a consent form. The subjects did not receive any financial reward for their participation.

2.2. Signal acquisition

Subjects 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). 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 at predefined locations on the EEG-cap marked with $P_Z, PO_3, PO_4, O_1, O_2, O_Z, O_9$ 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 kΩ. 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.

2.3. Signal processing

For SSVEP signal classification we used a minimum energy combination method (MEC) introduced in [23], as modified in [24].

The SSVEP response for a flickering frequency of f Hz, the voltage between the ith electrode and reference electrode at time t can be described as a sum of sine and cosine functions of the frequency f and its harmonics k, with corresponding amplitudes $a_{i,\,k}$ and $b_{i,\,k}$:

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

The term $E_{i,\,t}$ represents the noise component of the electrode i, describing various artifacts that cannot attribute to the SSVEP response. For a time segment length of T_s, acquired with sampling frequency of F_E Hz, containing N_t samples of the ith signal, the model can be described in vector form as $y_i = X\tau_i + E_i$ where $y_i = [y_i(1), \ldots, y_i(N_t)]^T$ is a $N_t \times 1$ vector and X is the SSVEP model matrix of size $N_t \times 2N_h$ containing the sine and cosine components. Further, the vector τ_i contains the corresponding amplitudes $a_{i,\,k}$ and $b_{i,\,k}$.

To cancel out the nuisance and noise, a channel vector s of length N_t is defined as linear combination of the electrode signals: $s = \sum_{i=1}^{N_y} w_i y_i = Yw$, where w is a vector of weights associated with the electrode signals. Introducing a set of N_s channels $S = [s_1, \ldots, s_{N_s}]$ the equation above can be generalized to $S = XW$, where $W = [w_1, \ldots, w_{N_s}]$ is the corresponding weight matrix.

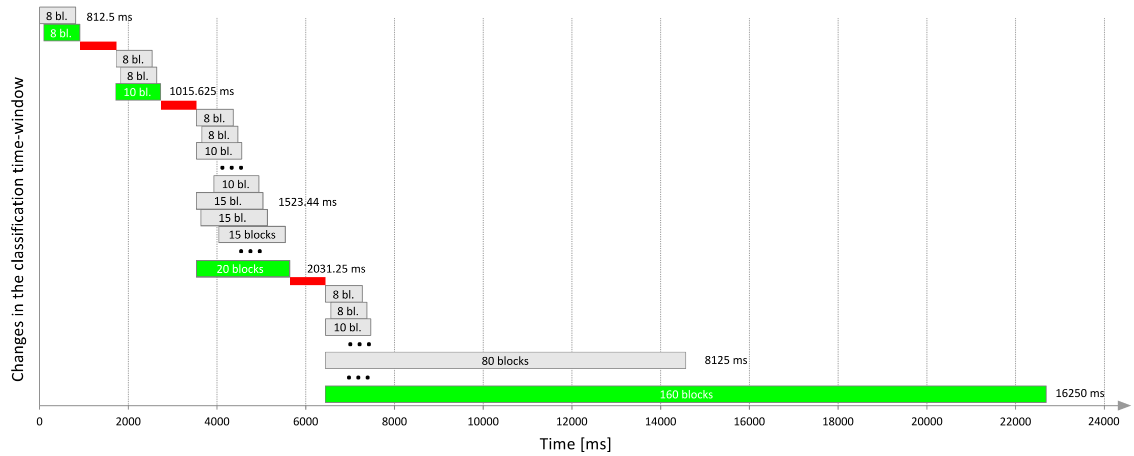

Fig. 1. Changes in the time window after a performed classification in case no distinct classification can be made and the actual time t allows the extension to the next pre-defined value. After each performed classification (green), additional time for gaze shifting was included (red) and the classifier output was rejected for 9 blocks. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

First, an orthognal projection is used to remove any SSVEP activity from the recorded signal,

$$\tilde{Y} = Y - X(X^TX)^{-1}X^TY.$$

Then a weights vector $\hat{w}$ that minimizes remaining signal $\tilde{Y}$ needs to be found: the solution of the optimization problem

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

is the smallest eigenvector v_1 of the symmetric matrix $\tilde{Y}^T\tilde{Y}$ and the energy of the resulting combination equals the smallest eigenvalue λ_1 from this matrix. Additional channels can be added by choosing the next smallest eigenvalues and corresponding eigenvectors and the weight matrix can be set to

$$W = \left[\frac{v_1}{\sqrt{\lambda 1}}, \ldots, \frac{v_{N_s}}{\sqrt{\lambda_{N_s}}}\right].$$

To discard up to 90 % of the nuisance signal the total number of channels is selected by finding the smallest value for N_s that satisfies the equation:

$$\frac{\sum_{i=1}^{N_s} \lambda_i}{\sum_{j=1}^{N_y} \lambda_j} > 0.1. \tag{3}$$

To detect the SSVEP response for a specific frequency, the power of that frequency and its harmonics N_h is estimated by

$$\hat{P} = \frac{1}{N_s N_h} \sum_{l=1}^{N_s} \sum_{k=1}^{N_h} \| X_k^T s_l \|^2. \tag{4}$$

To avoid overlapping of frequencies, we use $N_h = 2$ in the system implementation. The SSVEP power estimations for all N_f considered frequencies were normalized into probabilities,

$$p_i = \frac{\widehat{P_i}}{\sum_{j=1}^{N_f} \hat{P_j}} \text{ with } \sum_{i=1}^{N_f} p_i = 1,$$

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

In order to increase the difference between probabilities, a Softmax function was applied:

$$p_i' = \frac{e^{\alpha p_i}}{\sum_{j=1}^{j=N_f} e^{\alpha p_j}} \text{ with } \sum_{i=1}^{i=N_f} p_i' = 1, \tag{5}$$

Table 1
Overview of the used time segment lengths. Eleven segment lengths, T_s, between 812.5 ms and 16,250 ms were used.

Segment-length	Time [ms]	Blocks of EEG data (one block = 13 samples)
T_1	812.5	8 blocks
T_2	1015.625	10 blocks
T_3	1523.4375	15 blocks
T_4	2031.25	20 blocks
T_5	3046.875	30 blocks
T_6	4062.50	40 blocks
T_7	5078.125	50 blocks
T_8	6093.75	60 blocks
T_9	7109.375	70 blocks
T_{10}	8125.00	80 blocks
T_{11}	16250.00	160 blocks

with $\alpha = 0.25$. In order to increase robustness, three additional frequencies (means between pairs of target frequencies) were considered additional to the four target stimuli [19], hence $N_f = 7$. The classifier output O was then defined for $1 \le i \le N_f$ as

$$O = \begin{cases} \text{argmax}_i(p_i'), & p_i' \ge \beta_i,\ i \le 4 \\ 0 & \text{else.} \end{cases}$$

If no frequency probability exceeded the corresponding classification threshold β_i or if one of the additional frequencies ($i > 4$) had highest probability, the classification was rejected. For each stimulation frequency the experimenters determined classification threshold β_i individually during a familiarization run (see details in Section 2.5). After each classification the classifier output was rejected for the duration of 914 ms (9 blocks). During this gaze shifting period the targets did not flicker. The recorded EEG-data were processed in blocks of 13 samples (101.5625 ms with the sampling rate of 128 Hz).

The SSVEP classification was performed with the adaptive sliding window of T_s [24]. If no classification could be made and the actual time t allowed the extension of T_s to the next predefined value, this new value was used instead (see Fig. 1). Recently we modified the adaptive method further. In order to make the system more robust we increased the number of predefined time segment lengths to eleven (as displayed in Table 1).

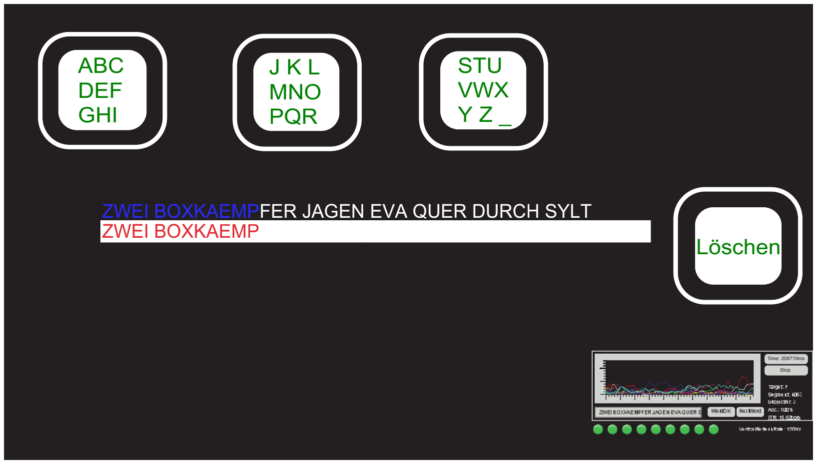

Fig. 2. GUI of the *Three-step spelling application* during the online experiment. A subject was spelling the text “ZWEI BOXKAEMPFER JAGEN EVA QUER DURCH SYLT” (a German pangram).

2.4. SSVEP-based Three-step spelling application

The *Three-step spelling application* resembles an earlier developed GUI [22,25,26]. In the *Three-step spelling application* four commands were represented on the computer screen by flickering boxes of default sizes (175 × 175 pixels). The size of the boxes varied during the experiment as described in [24]. The subject faced four boxes and in order to increase user friendliness, the user commands were displayed in the subjects mother tongue (German). Three boxes were arranged horizontally in the upper part of the screen containing the letters “A-I”, “J-R” and “S-_”, respectively. The additional 4th box, containing the command “Löschen” (delete the last spelled character) was located on the right side of the screen. The box for the written word and the word to spell was placed in the center of the screen. The content of the three boxes containing the alphabet changed to more specific sets according to the first selection made. The boxes would then display “A B C”, “D E F”, “G H I” or “J K L”, “M N O”, “P Q R” or “S T U”, “V W X”, “Y Z _”. After selection in this second window, the content of the boxes changed once more, and each box contained a single letter. In both the second and the third window, the far right box (“Löschen” in window 1) would contain the command “Zurück” (back), giving the user the option to switch to the previous window. At least three steps were necessary to choose any single letter. If the subject made a mistake, and corrected it with the command “Zurück” (back), the number of steps would increase. A screenshot of the first window taken during the online spelling task is shown in Fig. 2. In order to reduce the information load of the visual channel, every command classification was followed by an audio feedback with the name of the selected command or the letter spelled (also in German).

2.5. Experimental setup

After signing the consent form, each subject completed a brief pre-questionnaire, answering questions regarding gender, age and BCI experience. Afterwards the subjects were prepared for the EEG recording. Subjects participated in a familiarization run spelling the word “KLEVE”, and a word of free choice (e.g. the own first name). Next, each subject used the GUI to spell the German pangram “ZWEI BOXKAEMPFER JAGEN EVA QUER DURCH SYLT”. Stimulation frequencies and other SSVEP key parameters that were used in this experiment were determined individually on the basis of the refresh rate of the LCD screen (120 Hz) during the familiarization run. If repeated false classifications occurred during this test run, the experimenters manually adjusted the classification thresholds, or chose different frequencies. If the subjects had difficulties to select one of the buttons, the corresponding threshold β_i was lowered, or another frequency was used instead. Subjects spelled the word “KLEVE” with a predefined frequency set with frequencies between 6.67 Hz and 12.00 Hz. The frequency sets used for the pangram for each subject are provided in Table 2. Each spelling phase ended automatically when the presented word was spelled correctly. Spelling errors were corrected via the implemented delete button (“Löschen”). After the spelling phase the subjects completed a post-questionnaire, answering additional questions.

Table 2
Overview of the stimulation frequencies representing the commands used in the experiment. The frequency set was determined individually for each subject.

	Subject [#]	Command 1 [Hz]	Command 2 [Hz]	Command 3 [Hz]	Command 4 [Hz]
groupA	1	10.91	9.23	8	6.67
	2	10.91	10	8	6.67
	3	7.5	7.06	6.67	6.32
	4	10	7.06	6.67	6.32
	5	8	7.5	6.67	6.32
	6	8.57	8	7.5	6.67
	7	7.5	7.06	6.67	6.32
	8	7.5	7.06	6.67	6.32
	9	7.5	7.06	6.67	6.32
	10	6.67	7.06	7.5	8
groupB	11	9.23	8	7.06	6.32
	12	9.23	8	7.06	6.32
	13	8	7.5	7.06	6.32
	14	9.32	8	7.06	6.32
	15	8	7.5	7.06	6.32
	16	10	7.06	6.67	6.32
	17	6.67	7.06	7.5	9.23
	18	6.67	7.06	7.5	9.23
	19	6.67	7.06	7.5	8
	20	6.67	7.06	7.5	8

3. Results

BCI performance for each subject was evaluated by calculating the commonly used ITR in bit/min, employing the formula as discussed e.g. in [1]

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

where, B represents the number of bits per trial. The Accuracy P was calculated as the ratio between the number of correct and to-

Table 3
Results of spelling the task "ZWEI BOXKAEMPFER JAGEN EVA QUER DURCH SYLT" for *groupA*. All subjects were able to complete the task. C_N refers to the total number of commands, which is further divided into the number of correct and false commands, $C_{correct}$ and C_{false}, respectively. Min, Max, Mean and SD values are given at the bottom of the table.

Subject	Time	Acc.	ITR	Commands			Time/$C_{correct}$
	[s]	[%]	[bpm]	C_N	$C_{correct}$	C_{false}	[s]
1	402.49	99.22	36.66	128	127	1	3.169
2	633.24	95.21	22.75	146	139	7	4.556
3	885.93	97.76	16.41	134	131	3	6.763
4	491.97	100.00	30.73	126	126	0	3.905
5	449.72	100.00	33.62	126	126	0	3.569
6	500.09	99.22	29.50	128	127	1	3.938
7	860.74	95.77	16.62	142	136	6	6.329
8	577.99	100.00	26.16	126	126	0	4.587
9	466.27	98.48	31.62	132	130	2	3.587
10	499.79	99.22	29.52	128	127	1	3.935
Mean	576.82	98.49	27.36	131.60	129.50	2.10	4.434
SD	160.35	1.65	6.50	6.74	4.36	2.39	1.135
Max	885.93	100.00	36.66	146	139	7	6.763
Min	402.49	95.21	16.41	126	126	0	3.169

Table 4
Results of spelling the task "ZWEI BOXKAEMPFER JAGEN EVA QUER DURCH SYLT" for *groupB*. All subjects were able to complete the task. C_N refers to the total number of commands, which is further divided into the number of correct and false commands, $C_{correct}$ and C_{false}, respectively. Min, Max, Mean and SD values are given at the bottom of the table.

Subject	Time	Acc.	ITR	Commands			Time/$C_{correct}$
	[s]	[%]	[bpm]	C_N	$C_{correct}$	C_{false}	[s]
11	1841.23	79.65	6.90	226	180	46	10.229
12	1097.84	90.38	11.84	156	141	15	7.786
13	963.82	84.94	11.85	166	141	25	6.836
14	815.14	92.96	15.87	142	132	10	6.175
15	548.54	97.69	25.65	130	127	3	4.319
16	1287.30	87.26	12.31	212	185	27	6.958
17	702.31	96.27	19.57	134	129	5	5.444
18	737.65	94.37	18.43	142	134	8	5.505
19	1024.16	91.45	12.83	152	139	13	7.368
20	541.836	96.32	25.79	136	131	5	4.136
Mean	955.98	91.13	16.10	159.60	143.90	15.70	6.476
SD	372.51	5.44	5.90	31.58	19.87	12.74	1.708
Max	1841.23	97.69	25.79	226	185	46	10.229
Min	541.84	79.65	6.90	130	127	3	4.136

tal number of classified commands. In the GUI presented here, the overall number of possible choices was $N = 4$.

The overall BCI performance is given in Tables 3 and 4. All subjects were able to complete the spelling task. The overall distribution of time windows for all correct classifications is displayed in Fig. 3.

Fig. 4 provides the changes in signal power five seconds prior to a performed command classification. Provided are the averaged signals for stimulation frequencies used by subjects from each of the two age groups. Questionnaire results are given in Tables 5 and 6.

4. Discussion

All subjects achieved reliable control over the BCI system, reaching accuracies above 85%. It can be seen in Tables 3 and 4 that there is a substantial difference between the performance of younger subjects and subjects of advanced age. Subjects from *groupA* reached a mean accuracy of 98.49%. Three subjects from this group completed the spelling task even without errors, achieving an accuracy of 100%. The mean accuracy of *groupB* was 91.13% and no subject of this group reached 100% accuracy. A tudent's - test (with unpooled variance) revealed a significant difference between the mean ITR of young and elderly subjects, $t(11) = 3.88,\ p < 0.05$.

Also the time needed to complete the spelling task was noticeably larger for subjects from *groupB*. The mean ITR of *groupA* was 27.36 bit/min while subjects from *groupB* achieved a significantly lower ITR of only 16.19 bit/min ($t(18) = 3.85,\ p < 0.05$).

In the presented study the classification time window for subjects from *groupB* was usually larger (see Fig. 3). The graphs of the younger subjects are noticeably steeper in the last second prior to the command classification. The relevance of the choice of appropriate time segment lengths has been intensively discussed already in 2010 [19]. In a performance comparison on 8 different time segment lengths over 10 subjects the authors analyzed the distribution of the time segment length for all correct classifications and reported an average time segment length of 2.8 s for obtaining a SSVEP response recognition of 95%. The presented study confirms, that the implementation of larger time segments is beneficial for some users. Subjects from *groupB* needed to gaze at a stimulation frequency for relatively long time (see also Fig. 4). As displayed in Tables 3 and 4 subjects from *groupB* needed on average 6.476 s for a correct command classification; subjects from *groupA* needed on average 4.434 s which is significantly less according to a -test with unpooled variance ($t(16) = 2.98,\ p < 0.05$). A reason for the performance difference could be smaller SSVEP amplitudes of elderly people, similar to results of Hsu et al. [16]. They found that for stimulation frequencies 13, 15 and 17 Hz the young group reached SSVEP amplitudes of 2.82, 3.23 and 3.48 μV respectively. In comparison the elderly group reached amplitudes of 1.21, 1.28 and 1.67 μV for SSVEPs induced by the same frequencies. Regarding the amplitude of frontal SSVEPs, no significant difference was found among the groups. Meanwhile, in order to address performance difference between subjects and to maximize the classification accuracies, we developed a wizard that determines minimal time window length and classification thresholds individually for each user [27]; however, in the presented , the typical SSVEP parameters were determined manually by the experimenters.

Though the amplitudes of frontal SSVEPs might be generally smaller, they could be an alternative choice to design SSVEP-based BCIs especially for elderly people, as age related performance differences could be smaller with SSVEPs measured from frontal region. Other explanations for poorer performance might be that younger subjects had shorter reaction time and also faster learning ability compared to the subjects of advanced age.

It should also be noted that the performance gap could be even larger if a higher number of stimulation targets would be displayed, as the elderly people might have more problems with an increased information load of the visual channel. Minimizing the number of simultaneously displayed targets offers more freedom in stimulus size, distance between stimuli and also reduces the load on the visual channel so that less control of the users gaze direction is required. The drawback of a low stimulus number is relatively low ITR. Generally higher ITRs than in the presented study can be achieved with other BCI paradigms. Spüler et al. reported an average ITR of 144 bit/min and an accuracy of 96% using code-modulated visual evoked potentials (c-VEPs) and the detection of error-related potentials [28]. Visual stimulation with pseudo-random bit-sequences evokes specific Broad-Band Visually Evoked Potentials (BBVEPs) that can also be reliably used in BCI for high-speed communication in spelling applications [29].

An important issue regarding user comfort in SSVEP-based BCIs is frequency selection. All subjects participated in this study were asked about discomfort caused by flickering. 45% of the subjects stated that they found the flickering annoying; four of the elderly subjects even reported a slighly increased level of tiredness after the experiment (see Tables 5 and 6).

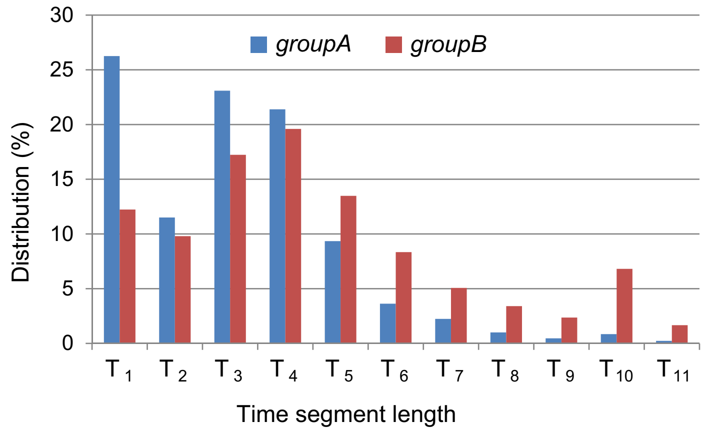

Fig. 3. Distribution of time segment lengths for all correct classifications in each age group. The distribution is displayed in blue for *groupA* (younger subjects), and in red for *groupB*. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 5
Results from the pre-questionnaires. The numbers are represented as number of respondents or in form: mean value (SD), range. The level of tiredness was rated on a scale from 1 to 5: (1) not tired, (2) little tired, (3) moderately tired, (4) tired, (5) very tired.

	Age	Gender		Vision correction		Level of tiredness					Length of sleep
	Years	M	F	Yes	No	(1)	(2)	(3)	(4)	(5)	Hours
groupA	22.4 (2.92), 17–27	6	4	3	7	2	2	6	0	0	6.25 (0.86), 5–7
groupB	67.3 (3.83), 64–76	3	7	10	0	3	4	2	1	0	5.61 (1.20), 3.5-7

Table 6
Results from the post-questionnaires as number of respondents. The level of tiredness was rated on a scale from 1 to 5: (1) not tired, (2) little tired, (3) moderately tired, (4) tired, (5) very tired.

	Level of tiredness					Flickering annoying	
	(1)	(2)	(3)	(4)	(5)	Yes	No
groupA	2	2	6	0	0	5	5
groupB	2	1	6	1	0	4	6

It is known that high-frequencies produce less visual fatigue than lower frequencies and show no stimulus-related seizures [30,31]. These crucial advantages might be even more important for elderly users. Detecting SSVEPs with high frequencies, however, is more challenging than detecting SSVEPs in the lower bands, as SSVEP amplitudes significantly decrease for high-frequency stimulation beyond 30 Hz [18]. Also the temporal stability of higher frequency components might require recalibration for each session [32]. Nevertheless, the performance drop due to higher stimulation frequencies might be weaker for elderly subjects. Further tests are necessary. Future work should address the performance gap caused by advanced age in more detail. GUIs could be modified to suit the needs of older users.

5. Conclusion

In this study, we investigated age associated SSVEP BCI performance differences by comparing results of a BCI spelling performance from two age groups. Experimental results based on twenty healthy subjects demonstrated that thanks to the implementation of large classification time windows (up to 16 s), every subject gained control over the system with decent accuracies. However, commands were classified faster and more accurate for subjects of the young group. The significant performance difference (mean ITR of 27.36 bit/min compared to 16.19 bit/min for the young and elderly age group, respectively) needs to be considered already during the design phase of BCI systems. The results confirm that subject age influence BCI performance, and indicate that GUIs should be modified to fit the needs of elderly users.

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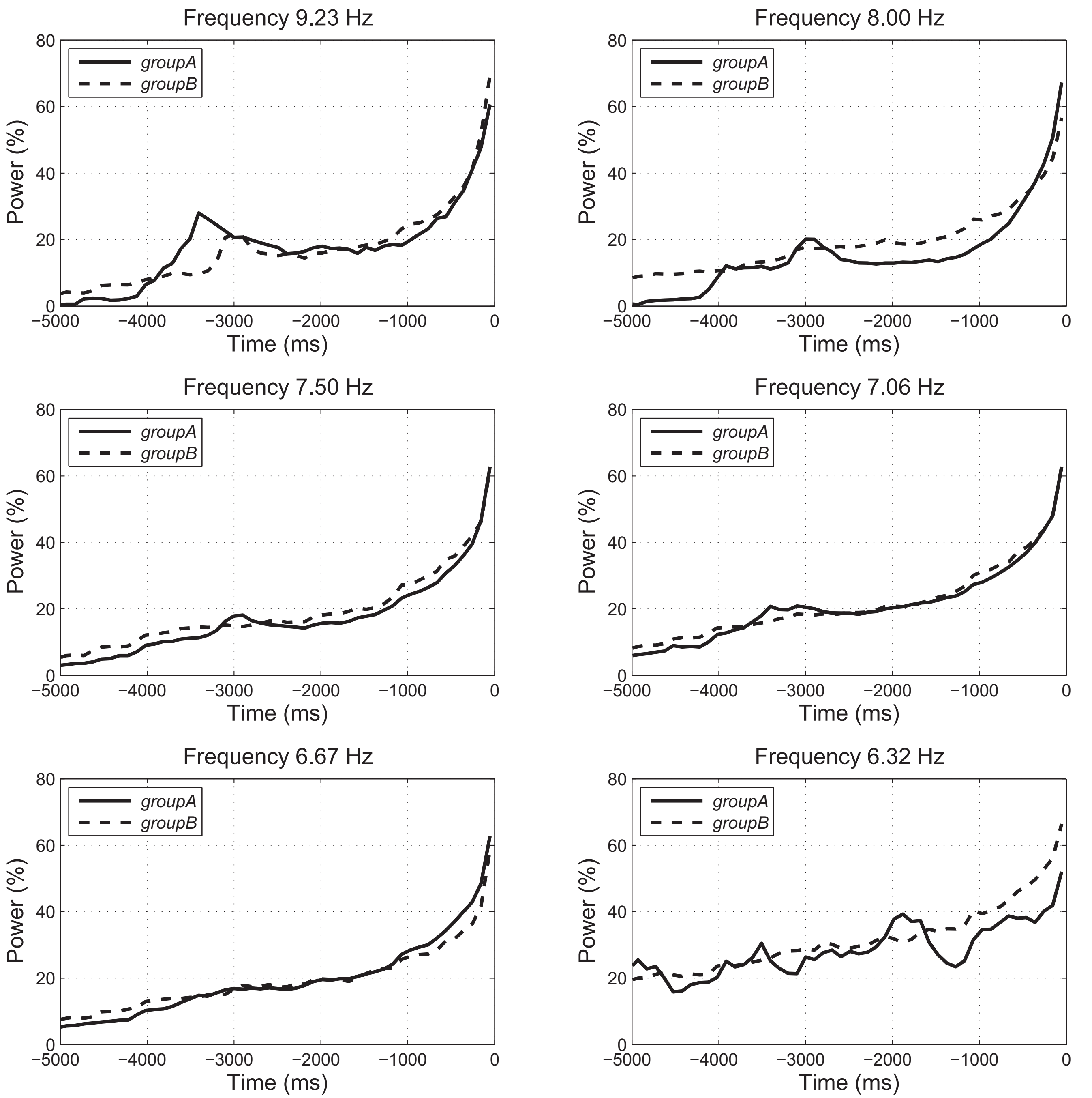

Fig. 4. Changes in signal power during command classification five seconds prior to a performed command classification. Provided are the averaged signals for selected stimulation frequencies used by subjects from each of the two age groups. The *x*-axis describes the time prior to a performed correct command classification; the *x*-axis limits were chosen based on the average command classification times. The *y*-axis describes the changes in the averaged frequency power estimations p'_i of the corresponding frequency prior to the correct classification of that frequency. The p'_i were averaged over all subjects and all performed correct commands of the corresponding frequency.

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