An Asynchronously Controlled EEG-Based Virtual Keyboard: Improvement of the Spelling Rate

Reinhold Scherer*, Gernot R. Müller, *Member, IEEE*, Christa Neuper, Bernhard Graimann, and Gert Pfurtscheller, *Member, IEEE*

***Abstract*—An improvement of the information transfer rate of brain-computer communication is necessary for the creation of more powerful and convenient applications. This paper presents an asynchronously controlled three-class brain-computer interface-based spelling device [virtual keyboard (VK)], operated by spontaneous electroencephalogram and modulated by motor imagery. Of the first results of three able-bodied subjects operating the VK, two were successful, showing an improvement of the spelling rate σ, the number of correctly spelled letters/min, up to $\sigma = 3.38$ (average $\sigma = 1.99$).**

***Index Terms*—Asynchronous control, brain-computer interface (BCI), motor imagery, virtual keyboard (VK).**

I. Introduction

COMMUNICATION and the ability to interact with the environment are basic needs for human relationships. For people who suffer from severe physical disabilities or palsy, the ability to comply with this need is limited or even impossible. In contrast to impaired motor activity, the sensory and cognitive functions are usually almost intact (locked-in state). Bioelectrical brain signals, such as those reflected by electroencephalogram (EEG) or electrocorticogram (ECoG), have been proved to provide an alternative communication channel. Intellectual activity can modify the bioelectrical brain activity without any motor action. A brain-computer interface (BCI) is able to recognize voluntary changes in the ongoing electrophysiological signals and to map different brain states to appropriate commands in order to operate communication aids [1]–[5].

Patients suffering from amyotrophic lateral sclerosis (ALS) learned to operate an electronic spelling device [1]. With a binary decision, which requires the discrimination of two different brain states (classes), the German alphabet was split iteratively, following a fixed procedure, into two halves until the desired letter was isolated. The communication performance, given by the spelling rate σ and measured in correct selected letters/min, reached values of about 0.5 letters/min ($\sigma \approx 0.5$). Using the same letter selection strategy, a patient suffering from severe cerebral palsy achieved spelling rates of approximately one letter/min ($\sigma \approx 1$) controlling the Graz-BCI [6]. To improve the spelling rate (σ) or, more generally, to increase the information transfer rate is a main goal in BCI research.

The aim of this paper is to introduce a new Graz-BCI based spelling application designed to provide an increase in the information transfer rate. The basic principle of the Graz-BCI is the classification of sensorimotor EEG patterns generated by the imagination of motor activity (e.g., left hand, right hand, foot, or tongue) [4], [7]. The setup of the classifier is done by performing a cue-based repetitive training of mental motor imagery. During the following feedback training, the real-time classification result of the ongoing EEG is presented to the subject (e.g., moving cursor). By repeating this training and updating the classifier, the subject and the BCI can mutually adapt to one another.

The following points were taken into account for the implementation and design of the virtual keyboard (VK).

1) *Improvement of the classification accuracy:* Since biological signals show a large inherent variability, the reliability of a classifier is very important. The adaptation and optimization of the parameters of the selected information processing methods should lead to a better generalization and, consequently, to a reduction of misclassification.
2) *Increase of the number of discriminable brain patterns:* An increase of the number of brain patterns that can be equally reliably detected may increase the communication speed. If the two-class process described above is divided in three instead of two parts, less selection steps are necessary.
3) *Noncue-based (asynchronous) information transfer:* The real-time Graz-BCI operates in a cue-based or synchronous communication mode [4], [7]. If the BCI (receiver) is prepared to handle an input, a ready signal (cue) is sent to the user (transmitter). Therefore, cue-based communication requires an additional signal to enable a proper information transfer. A side effect is an idling period, in which the user and the BCI are waiting. Besides this synchronous transfer mode, asynchronous transfer is also possible. In the latter case, no additional signal is required, since all the information is already contained in the conveyed signal. The BCI processes the incoming physiological signals and reacts properly if a known input pattern is found [8], [9]. From an engineering point of view, the asynchronous mode is more

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TABLE I
OVERVIEW OF SELECTED ELECTRODE POSITIONS ACCORDING TO INTERNATIONAL 10–20 SYSTEM. DEVIATION FROM PREDEFINED POSITION IS GIVEN AS ANTERIOR (+) OR POSTERIOR (−) DISTANCES IN CENTIMETERS. FOR SUBJECT l1 AND O3, ELECTRODE DISTANCE WAS 5 CM, AND FOR SUBJECT k3 WAS ONLY HALF (2.5 CM)

Subject	Electrode position
k3	(C3+2.5, C3), (Cz, Cz-2.5), (C4+2.5, C4)
l1	(C3+2.5, C3-2.5), (Cz+2.5, Cz-2.5), (C4+2.5, C4-2.5)
o3	(C3+2.5, C3-2.5), (Cz+2.5, Cz-2.5), (C4+2.5, C4-2.5)

difficult to handle than the synchronous. For the user, however, it does reflect the behavior of dialog partners in a good conversation, that is the coordination of timing and speed.

With an asynchronously controlled three-class VK, copy spelling experiments were performed and first results of three able-bodied subjects are reported.

II. METHODS

A. Subjects and Data Acquisition

Three healthy subjects familiar with the cue-based two-class Graz-BCI VK participated in this study. Each subject was seated in a comfortable armchair located about 1.5 m in front of a computer screen. Three bipolar EEG-channels were recorded from six gold electrodes placed over the cortical hand and foot area according to the international 10–20 system. The exact electrode position for each subject is summarized in Table I. It is important to note that subject k3 had smaller electrode distances (2.5 cm) compared to l1 and o3 (5.0 cm). This is the result of previous experiments, where an improvement of the classification accuracy was found with smaller electrode distances. The EEG was band-pass filtered between 0.5 and 30 Hz and recorded with a sample frequency of 128 Hz.

B. Controlling the Graz BCI

1) Training Paradigm: The training consisted of a repetitive process of cue-based movement imagery trials. The standard two-class Graz-BCI training paradigm [4] was modified and adjusted in order to handle three classes: "left hand," "right hand," and "foot" movement imagination. The duration of each trial varied randomly between 8 and 10 s and started with a blank screen. At second 2, a short warning tone was presented and a fixation cross appeared in the middle of the screen. From seconds 3–7 an arrow (cue) was shown, indicating the mental task to be performed. An arrow pointing to the left, to the right, or downward indicated the imagination of a left hand, right hand, or foot movement, respectively. The order of appearance of the arrows was randomized and at second 7 the screen was cleared [Fig. 1(a)]. Two sessions were recorded for each subject on different days. Each session consisted of three runs with 30 trials each (ten trials per class).

During the feedback training, the subjects had to learn to control a cursor placed in the middle of the screen. On the left side, right side, and below the cursor three randomly selected letters were visible. The task was to move the cursor toward the previously highlighted letter [Fig. 1(b)]. Two feedback runs where performed from each subject with 30 trials each (ten trials per class).

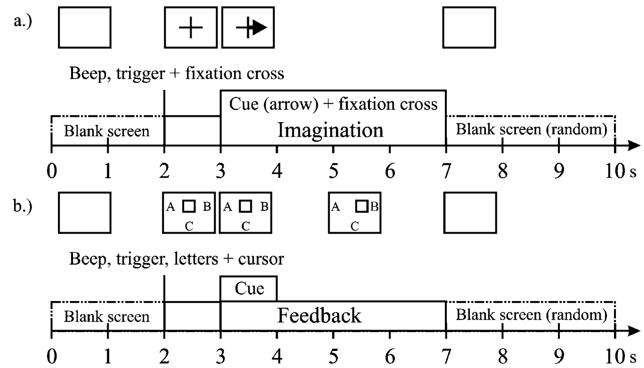

Fig. 1. (a) Training and (b) feedback paradigm. (a) At second 2, a warning tone was presented and a fixation cross appeared. From seconds 3–7, subject had to imagine a motor activity according to the presented cue (arrow). (b) At second 2, visual feedback (cursor) and three randomly selected letters were visible (on the left side, right side, and below the cursor). Goal was to move the cursor (from seconds 3–7) into the direction of previous highlighted letter (seconds 3–4). Target is the letter "B..

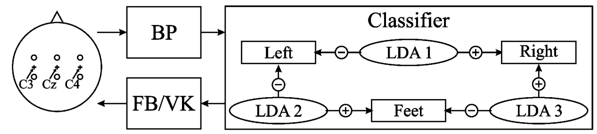

Fig. 2. Online BCI feedback loop: bandpower features (BP) were extracted from the ongoing EEG, classified, and result was passed to the feedback training (FB) or the virtual keyboard (VK) spelling application. Classifier consisted of three LDA discriminant functions, each trained to distinguish between two different movement imagery related brain patterns (e.g., LDA1 left versus right hand). Sign of the classification result indicates class affiliation (negative ⊖ versus positive ⊕). Classifier output was computed according to Table II.

2) Feature Extraction and Classification: For online processing, logarithmic band-power (BP) features were extracted from the ongoing EEG and classified using Fisher's linear discriminant analysis (LDA). The BP estimate was computed by digitally bandpass filtering the EEG, squaring the signal, and averaging the samples over a predefined period. As in previous experiments [10], two frequency bands were selected and applied to each EEG channel (six BP features).

The three-class discrimination problem was solved by combining three LDA discriminant functions. Each function was trained to distinguish between two different motor imagery brain patterns. The classifier output was computed by logically combining the single LDA results. Fig. 2 shows the real-time BCI feedback loop used for the experiments and the interrelationship between the LDAs. The logical state table of the classifier is reported in Table II. The criterion for the classifier output was the independent detection of the same EEG-pattern of two LDAs. This procedure was adopted with the aim to increase the robustness and reliability of the classifier. The deflection of the cursor was computed by averaging the LDA distance values of the two LDAs involved in the classification result. If no pattern could be detected, the value was set to zero (initial position).

3) Feature Selection: The BP estimates are dependent on the bandpass frequency band, on the number of samples used for the averaging, and the time within the motor imagery period.

TABLE II
LOGICAL STATE TABLE OF CLASSIFIER. SIGN OF EACH LDA CLASSIFICATION RESULT IS AN INDICATOR OF CLASS AFFILIATION. INPUT FEATURES BELONG TO CLASS 1 FOR NEGATIVE VALUES $\ominus$ AND TO CLASS 2 FOR POSITIVE VALUES $\oplus$. BRAIN PATTERN WAS CLASSIFIED ONLY IF TWO LDAS WERE ABLE TO DISCRIMINATE THE SAME PATTERN INDEPENDENTLY. FEEDBACK PARAMETER WAS COMPUTED BY AVERAGING TWO LDA DISTANCE VALUES INVOLVED IN CLASSIFICATION RESULT. OTHERWISE, VALUE WAS SET TO ZERO. (SEE ALSO FIG. 2)

LDA 1	LDA 2	LDA 3	classification result
$\ominus$	$\ominus$	$\ominus$	Left hand
$\oplus$	$\ominus$	$\ominus$	Not classified
$\ominus$	$\oplus$	$\ominus$	Foot
$\oplus$	$\oplus$	$\ominus$	Foot
$\ominus$	$\ominus$	$\oplus$	Left hand
$\oplus$	$\ominus$	$\oplus$	Right hand
$\ominus$	$\oplus$	$\oplus$	Not classified
$\oplus$	$\oplus$	$\oplus$	Right hand

TABLE III
RANGE OF BP PARAMETERS USED FOR GA OPTIMIZATION

Feature	Range	Stepsize
Time	sec. 2 to sec. 8	1/sample rate
Frequency band	5 to 40 Hz	1 Hz
Averaging period	64 to 192 samples	1 sample

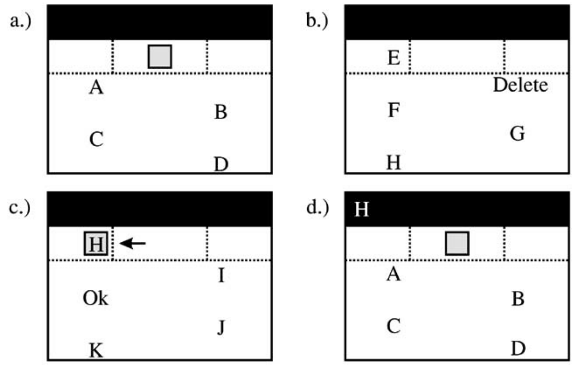

Fig. 3. Graphical user interface of VK. (a) Small upper part (black area) is used for presentation of spelled letters and the remaining big part (white area) is required for letter selection process. Visual feedback is given by a cursor (gray square). Below the cursor, two assembly lines, one on each side, carrying the alphabetically sorted letters are visible. To avoid disturbing influences, letters on left and right side were vertical displaced. Example: Selection of the letter "H." (b) Pass through the letters by performing an ongoing foot motor imagery until the desired item is visible on the left or right side of the screen. Cursor disappears from the screen in order to give subject the opportunity to concentrate on letters. (c) Letter, which exceeds the horizontal line below the cursor, becomes highlighted and can be selected by moving the cursor toward its direction. VK accepts letter if cursor had exceeded subject-specific left or right threshold (vertical lines on the left and right side of the screen) for a subject-specific period (continuous left-hand or right-hand motor imagery). (d) Selected letter appears in text region and letter selection process can start again. Note, in parts (b) and (c), appearance of control commands DELETE and OK.

The problem was to find suitable parameter values able to minimize misclassification. The parameter ranges taken into account are summarized in Table III. About $5.8 \cdot 10^9$ combinations were possible, and therefore the setup of the classifier was done by a genetic algorithm (GA)-based optimization process [11]. The optimization task was to find two BP features, suitable for each channel, with two nonoverlapping frequency bands, but with the same averaging and time values. The averaging period and the point in time were encoded into integer values. The frequency bands gene consisted of four discrete values, representing the lower and upper cutoff frequencies of the two nonoverlapping bands. From two parents, three offspring were recombined: two by interchanging the lower band and one by averaging the upper and lower band, respectively. Mutation varied the bandwidth of either the lower or upper band by randomly changing one cutoff frequency. For 20 different populations (initial size 80, offspring 50 individuals), the GA was repeated for 100 generations with a mutation rate of 0.02. The individuals were selected according to the rank selection method. The minimization of the mean value of the three LDA classification error rates was selected as optimization criterion (fitness function). The error rates were computed by a 10×10-fold cross-validation LDA training. In contrast to the general attempt to reduce the computational effort of the fitness function, the cross-validation training was relatively time consuming. However, the expectation of this procedure was a better generalization performance of the classifier.

The GA was applied to the motor imagery training sessions (without feedback).

4) Asynchronous Control Strategy: During the feedback experiments, the classifier, trained with the parameters obtained by the GA, was applied to the ongoing EEG sample by sample. In this way, 128 decisions were computed each second. However, only each twelfth sample was used for the feedback generation (approximately ten screen updates per second). The resulting class information stream was mapped to the position of the feedback cursor. The subject was able to move the cursor without the constraints of a fixed timing scheme. Based on this control mechanism, the new graphical user interface for the VK was developed.

C. Virtual Keyboard

1) Design and Operation: The screen was divided into two parts: a small upper part (about 20%) was used for the presentation of the selected letters and words, respectively, while the letter selection process and the visual biofeedback (cursor) used the remaining lower part. A total of 26 letters, taken from the German alphabet, were arranged alphabetically on two moving assembly lines on the left and right half of the screen. A vertical displacement between the letters on both sides should avoid the sensation of competition between the items [Fig. 3(a)]. Every five letters, a control command was inserted: DELETE, used to delete the last spelled letter and OK to confirm the spelled word. Five items were visible on each side. As long as foot motor imagery (class 3) was detected, the items scrolled from the bottom to the top of the screen. The scrolling speed was associated with the movement of the cursor. The higher the distance from the origin, the faster was the speed of the scrolling. If an item reached the top of the selection area it disappeared and a new one appeared from the bottom. In order to avoid disturbing influences and give the subject the opportunity to concentrate on the moving objects, the feedback cursor was hidden during the scrolling process [Fig. 3(b)]. The item on the topmost position could be selected by moving the feedback cursor toward the desired left or right direction by performing a left- or right-hand movement imagination (class 1 and 2). A confirmation of the selection occurred, if the cursor had exceeded a subject-specific left or right side threshold for a subject-specific time period [Fig. 3(c)]. The selected letter was presented in the

TABLE IV
OFFLINE RESULTS OF GA-BASED OPTIMIZATION OF TRAINING WITHOUT FEEDBACK SESSIONS. FOR EACH SUBJECT, BEST CLASSIFICATION TIME (FROM BEGINNING OF TRIAL), CORRESPONDING FREQUENCY BANDS, AND NUMBER OF SAMPLES TO AVERAGE ARE SUMMARIZED. THE CLASSIFICATION ERROR VERSUS THE CLASSIFICATION ERROR ACHIEVED WITH STANDARD BANDPOWER VALUES (10-12 HZ AND 16-24 HZ AND 128 SAMPLES) IS SHOWN FOR COMPARISON

Subject	Time	Frequency bands	Average	Error	Std. err.
k3	5.29 s	9-14, 24-38 Hz	177	3.33%	5.33%
l1	4.77 s	11-28, 29-37 Hz	142	5.66%	23.00%
o3	5.05 s	10-15, 23-38 Hz	161	10.94%	17.03%

upper part of the screen and the spelling procedure could start again [Fig. 3(d)].

2) Copy Spelling: Directly after the feedback training (Section II-B1), the subjects had to exercise to control the VK by spelling their own name. During this period, the subject-specific parameters were adjusted. The left- and right-side threshold was set to the class-specific mean value of the LDA distances. The scrolling speed was adjusted according to the indications specified by the user. Subsequently, a copy spelling training, in which no wrong letter was accepted by the system ("error-ignoring" mode) was performed using the German words BITTE (please), HELFEN (help), HUNGRIG (hungry), BRAUCHEN (need), and SCHMERZEN (pain). The entire feedback and copy spelling training (third session) lasted about 2 h.

The copy spelling test was performed on another day (fourth session). The subject had the task of spelling the previously exercised German words BITTE, HELFEN, HUNGRIG, BRAUCHEN, and SCHMERZEN.

III. RESULTS

The feature parameters, extracted from the training sessions by the GA-based optimization process, are summarized in Table IV. Compared to subject l1, the frequency components for subject k3 and o3 are very similar. The same holds for the classification time and the averaging value. In addition, the best classification accuracy, computed for each sample within the motor imagery period (from seconds 3–7) using the standard BP parameters (10–12 and 16–24 Hz averaged over 1 s), is reported. The improvement of the classification performance is clearly visible in the decrease of the error rate: 2.00% for k3, 16.34% for l1, and 6.09% for o3. The classifiers built with the parameters found were working properly with new data also. Fig. 4 shows the time courses of the error rate of the online feedback runs. For the period relevant for motor imagery, the best classification performance is 5.00% error for k3, 3.33% for l1 and 6.67% for o3.

The copy spelling results are shown in Table V. The mean spelling time in seconds for a letter (t_{mean}) was computed by dividing the time needed to complete the word by the length of the word. Consequently, the spelling rate, or the correctly selected letters/min (σ), was $\sigma = 60/t_{\mathrm{mean}}$. The best σ was 3.38 for subject k3 and 2.85 for l1. During the session, subject k3 made only two spelling errors, while at least one error per word occurred for l1.

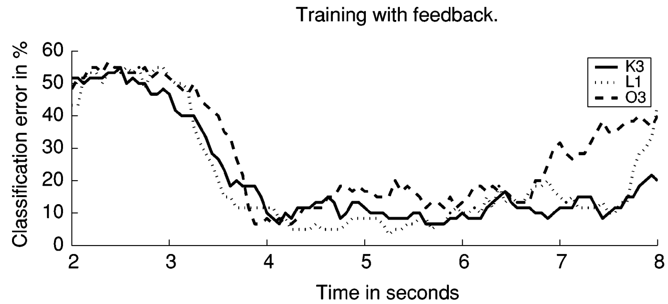

Fig. 4. Classification error curves of online feedback training. Classifier, setup from the GA for each subject, was working properly with new and unknown data. Beginning with second 3 (cue presentation), classification error decreased until second 7 (end of feedback presentation).

TABLE V
COPY SPELLING RESULTS FOR SUBJECTS k3 AND l1. SPELLING TIME IN SECONDS, NUMBER OF MISSPELLED LETTERS, AND RESULTING SPELLING RATE σ IN LETTERS PER MINUTE IS REPORTED

	k3			l1		
Word	$t_{spelling}$	err.	σ	$t_{spelling}$	err.	σ
BITTE	163.46	0	1.84	105.13	1	**2.85**
HELFEN	136.82	0	2.63	184.87	3	1.95
HUNGRIG	266.39	1	1.85	242.99	2	1.73
BRAUCHEN	141.87	0	**3.38**	448.09	3	1.07
SCHMERZEN	265.18	1	2.04	990.81	9	0.54
Mean			2.35			1.62

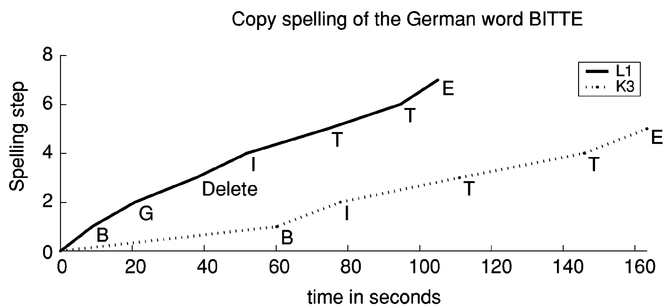

Fig. 5. Spelling performance for word BITTE. Subject k3 missed the first letter "B" and had to browse through entire alphabet. Subject l1 selected a wrong letter and had to correct this mistake.

Subject o3 was not able to correctly spell a single word. The first letters could be selected without any problem, but the longer the duration of the copy spelling run, the worse the control. The experiment had to be interrupted. Instead of the copy spelling, a cue-based feedback training was performed (one run of 30 trials). The analysis of the data showed classification error rates comparable to the previous feedback training (Fig. 4). The good separability of the EEG-patterns was overlapping with the subjective impression stated by o3 to be able to control the feedback cursor. Although the subject was able to handle the cue-based operation mode, the asynchronous mode could not be controlled for a longer period.

Fig. 5 shows the copy spelling performance of the word BITTE. Subject k3 completed the word in 163.46 s without any spelling error. One error, however, was made during the scrolling function. The first letter "B" was missed and k3 had to go through the entire alphabet until the letter reappeared. This explains the 60 s used for the first letter. Subject l1 made an incorrect selection with the second letter "I" and chose the

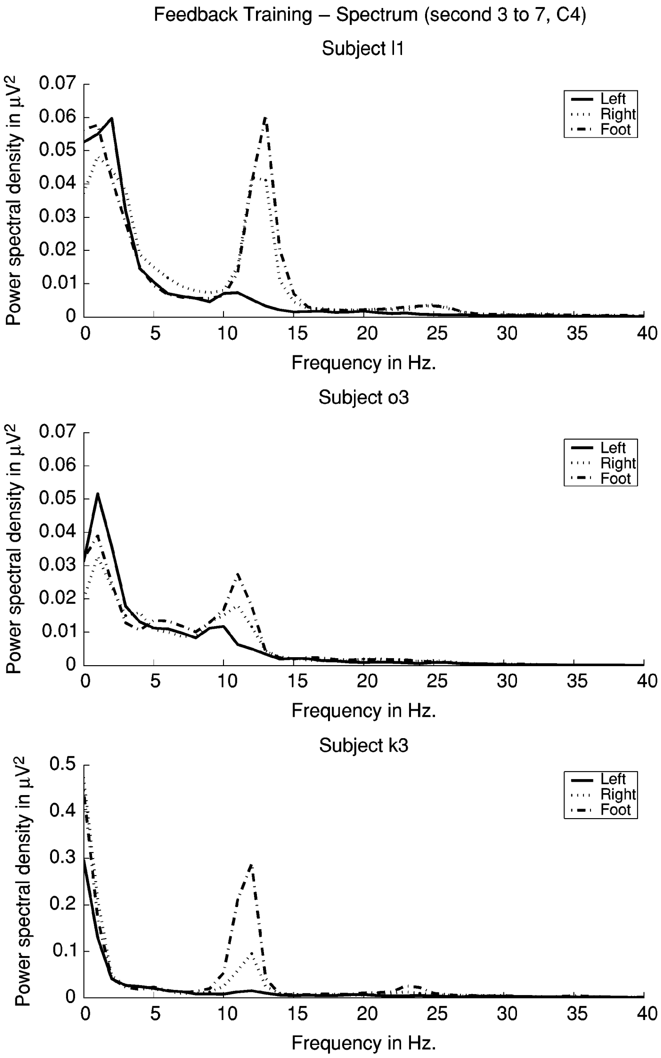

Fig. 6. Power spectral density for channel C4. Each plot shows subject specific power spectra of motor imagery period during online feedback experiment. Values for subject k3 vary because of different electrode arrangement and amplifier gain settings. No evidence of muscle artifacts is visible.

antecedent letter "G" instead,. This implied two additional spelling steps: deleting the misspelled letter and choosing the correct one. The word was correctly spelled in 105.13 s. Although l1 made two more selections, the spelling rate was higher.

The curves in Fig. 6 show for each subject the spectral density of the EEG recorded over C4 during the online feedback experiment. The spectra were computed by averaging the single trial spectra of the motor imagery period. No evidence of muscle artifacts is visible. The spectral density values of subject k3 are different because of the smaller electrode distances and amplifier gain settings.

IV. Conclusion

The mean overall spelling rate, for the two successful users, of 1.99 letters/min ($\sigma = 1.99$) seems to indicate an improvement compared to the earlier cue-based version of the VK, given that the best performance of able-bodied subjects varied between 0.50 and 0.85 letters/min (fixed trial length of 8 s) [12]. For trial-based applications, the information transfer rate can be computed according to the formula proposed in [13]. For the asynchronous selection of letters, however, several successive and therefore no longer independent classification results have to be considered. Consequently, the proposed formula cannot be applied. As a measure of performance, the spelling rate σ was computed.

The spelling of the word BITTE demonstrates that new control and selection strategies had to be acquired by the subjects. With the two-class VK and the dichotomous letter and command selection procedure, a misspelling induced a longer series of correction steps [12]. The new design combines letters and control commands and corrections can be done much faster.

The GA-based optimization of the input features proved to be a suitable tool because the selected subject specific BP parameters clearly improved the classification performance compared to the use of the standard values. However, the relatively high-frequency components of the second band for each subject were surprising (Table IV). A possible explanation for the higher beta bands is the optimization task assigned to the GA: it was to find two different frequency bands within the range between 5 and 40 Hz. Further analysis of the feature relevance should give more details. Because of the involvement of the higher frequency bands, special care in avoiding muscle artifacts was taken. The inspection of the recorded EEG signal and the frequency spectra confirmed that the cursor control definitely was not based on muscle activity (Fig. 6).

Of interest is that only two out of three subjects, all familiar with BCI-experiments, were successful in operating the asynchronous VK. This is surprising because all three subjects had classifiers with an error rate of around 10% and were able to control the feedback cursor. One possible reason might be the short training period (one session only). The asynchronous three-class VK is more cognitively demanding than the two-class cue-based version. This is also visible in the variability of the spelling time. No consistent spelling performance could be achieved. More training will possibly lead to better results. An alternative explanation is the distracting effect of the new visual presentation. Compared to the two-class version, in which the screen content was static during a trial and only the feedback was moving within the predefined period, a dynamic scenario with several moving objects was presented. The visual input has a strong impact on motor cortex activity [14] and can lead to a deterioration or changing of the motor imagery related EEG patterns. More research on this effect is neccessary.

The new design holds the potential to further increase the spelling rate. At the same time, however, multiple classes and asynchronous control can limit the usability of the system. Users do require more training and the cognitive load is higher. The latter demand poses the problem that the new spelling system is not equally suited for all people. Users that are able to handle the demands, however, can benefit from a higher information transfer rate.

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