A NOVEL CALIBRATION METHOD FOR SSVEP BASED BRAIN-COMPUTER INTERFACES

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ABSTRACT

A brain-computer interface (BCI) provides the possibility to translate brain neural activity patterns into control commands without user's movement. In recent years, there has been increasing interest in using steady-state visual evoked potential (SSVEP) in BCI systems. The SSVEP based BCI system requires several simultaneously flickering light sources of distinct frequencies, enabling the user to interact by focusing on one of the stimuli. However, the amplitude of the SSVEP is not the same for different stimulation frequencies or for different subjects. In order to find optimal stimulation frequencies, stimuli are usually processed sequentially; this can take several minutes. This paper introduces a novel multi-target calibration method for SSVEP-based BCIs, which allows significant shortening of the calibration procedure. This approach was successfully evaluated in 5 neurologically intact subjects, shorting the calibration time by four. No major influence on the quality of calibration could be observed.

1. INTRODUCTION

BCI systems allow people to communicate through direct measures of brain activity [1]. These devices may be the only possible way of communication for severely disabled users, such as persons with cerebral Palsy, after stroke, or injuries to the brain or spinal cord. Recent studies have indicated an increased interest in non-invasive BCI systems, which can be based on various sensory modalities [8]. In non-invasive BCIs, electroencephalography (EEG) is commonly utilized because of its high time resolution, ease of acquisition, and lower cost when compared to other brain activity monitoring modalities. In recent years, there has been increasing interest in using steady-state visual evoked potential (SSVEP) in BCI systems; the SSVEP approach provides up to date the fastest and most reliable communication paradigm for the implementation of a non-invasive BCI system [9, 11]. However, many aspects of current system realizations need improvement, specifically in relation to speed (in terms of information transfer rate as well as time needed for performing a single command), user variation and ease of use.

An SSVEP-based BCI system must reflect the user attention to a fast oscillating stimulus. The stimuli are lights flickering at different frequencies and their responses in the EEG signals correspond to SSVEPs at the same frequencies as the stimuli and their harmonics. The best responses for these signals are obtained for stimulation frequencies between 5 and 20 Hz [7]. The amplitude that characterizes an SSVEP response depends on the frequency, intensity and the structure of the repetitive stimulus. Some studies have compared the spectrum differences between a variety of stimuli sources, e.g. between light emitting diodes (LED) and monitors [10, 12]. The amplitude of the SSVEP responses evoked by LEDs are significantly larger than the evoked by stimuli presented on a computer monitor. Current SSVEP based BCIs use one-to-one correspondence between stimulating frequency and the command, hence a large number of choices such as in a virtual keyboard requires a large number of frequencies. *Gao et al.* observed that two flickering targets with a difference in frequency of 0.2 Hz can be successfully distinguished in the EEG signals, which allowed them to develop an online SSVEP BCI system with 48 targets [3]. However, the amplitude of the SSVEP is not the same for different stimulation frequencies and for different subjects [6] (as seen in Fig. 1). Therefore, to obtain optimal subject parameters an additional calibration phase is required [4]. During an extensive analysis of recently published works we realized that ALL research groups perform the training phase in order to select the best individual frequencies (and of course to optimize the spatial filtering and other parameters needed for real-time processing in the online SSVEP-based BCI system) in sequential way, this chain calibration usually takes several minutes.

Mukesh et al. suggested the so-called dual stimulation technique in order to increase the number of BCI commands by using a suitable combination of frequencies [5]. They found that for some frequencies spectral peaks of the combination frequencies were predominant compared to individual stimulating frequencies. This method increases the number of selections by using a limited number of stimulating frequencies in BCI. This idea did not find a broad application, because this method did not cause the direct increase of the accuracy of signal classification and furthermore, it is possible to produce any number of stimulating frequencies with modern hardware.

Derived from this idea, we propose a novel multi-target technique for the selection of individual subject-dependent stimulating frequencies to be used in any online SSVEP-BCI system. This method provides a significant shortening of the calibration procedure. The aim of the present study is to investigate the feasibility of suitable combination of frequencies for visual stimulation in order to significantly shorten the duration of the training phase in SSVEP-based BCIs.

This paper is organized as follows: The second section presents the experimental protocol used in the study. Two methods to evaluate the effectiveness of the proposed calibration method are presented. Results shows analyses conducted in frequency and time domains and resulting frequencies obtained for each subject. Discussion and conclusion are presented in the final section.

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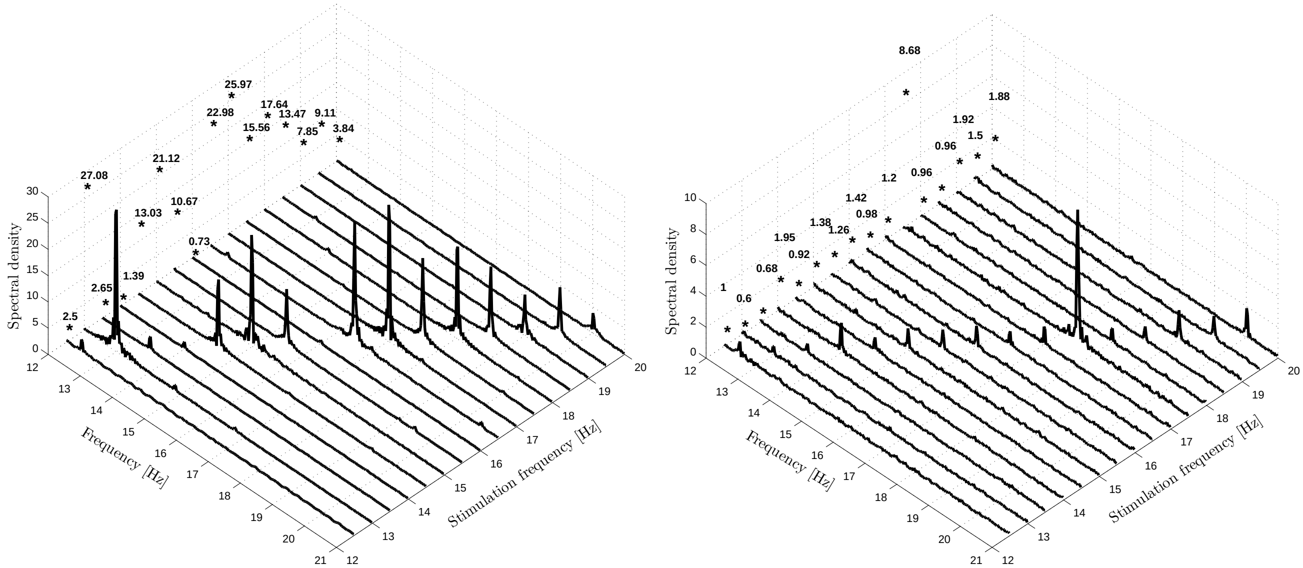


(a) Subject 3 (b) Subject 5

Figure 1: Differences in frequency spectrum for Subjects 3 and 5. EEG signals were acquired during sequential visual stimulation with 16 individual flickering frequencies ranged from 12.5 to 20 Hz (with a 0.5 Hz steps) at the PO_4 electrode. The SSVEP response can observed as peaks at each of the stimulating frequencies.

2. METHODS

2.1 Subjects

A total of 5 subjects participated in the study. Subjects' mean age was 26 years, range 22-29 with standard deviation 2.92. None of the subjects had neurological or visual disorders, other than refractive errors. Spectacles were worn when appropriate. All subjects were used to a computer screen for their daily work. Subjects did not receive any financial reward for participating in this study.

2.2 Data acquisition

The experiments were carried out in a normal office room of the Institute of Automation at the University of Bremen. This is different to the usual EEG recording conditions, in which an electrically shielded room with low background noise and luminance is usually used. Subjects sat in a comfortable chair. A LED stimulator shown in Fig. 2 was placed approximately 25 cm from the subject. EEG data were recorded from the surface of the scalp via eight sintered Ag/Ag-Cl EEG electrodes. They were placed on AF_Z for ground, right ear lobe was used for the reference electrode and $P_Z, PO_3, PO_4, O_Z, O_9, O_{10}$ as the input electrodes based on the international system of EEG measurement. The standard abrasive electrolytic electrode gel was applied between the electrodes and the skin to bring impedances below 5 $k\Omega$. An EEG amplifier g.USBamp (Guger Technologies, Graz, Austria) was used for signal acquisition. The sampling frequency was 128 Hz. During the EEG acquisition, an analog bandpass filter between 2 and 30 Hz, and a notch filter around 50 Hz (mains frequency in Europe) were applied directly in the amplifier.

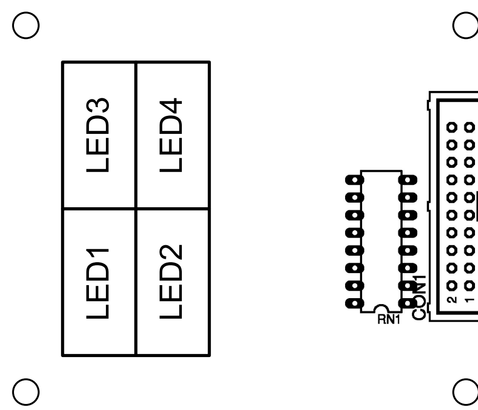
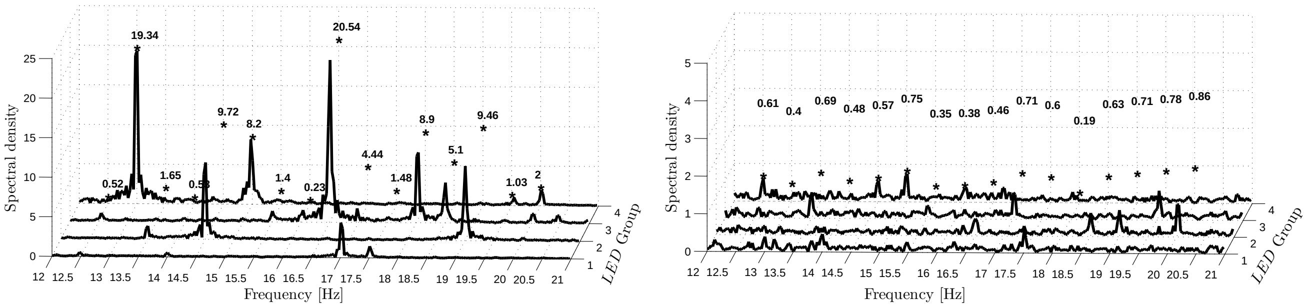


Figure 2: LED stimulator. The four red LEDs (modules HLMP-2685, size 10x20 *mm* each) with common luminance of around 2.56 *cd*.

2.3 Experimental Protocol

Subjects were instructed to look at the LED stimulator while EEG data were collected. The experiment consists of two runs with a short resting time in between. During each run the user was stimulated with 16 different frequencies (ranged from 12.5 and 20 Hz with 0.5 Hz steps). In the first run, only LED1 (see Fig. 2) was flickering with different stimulation frequencies, each frequency was randomly selected. The stimulation time was determined randomly and varied from 21 to 25 seconds. Between the stimulation of two different frequencies, there were short breaks that varied from 5 to 7 seconds. In the second run, the user was confronted with four simultaneously flickering LEDs (LED1-LED4 in the Fig. 2) presenting 4 stimulating frequencies at once.



(a) Subject 3

(b) Subject 5

Figure 3: Differences in frequency spectrum (for Subjects 3 and 5) from EEG signals acquired during visual stimulation with 4 groups of 4 LEDs, each with flickering frequencies ranged from 12.5 to 20 Hz (with a 0.5 Hz steps) at the PO_4 electrode. The SSVEP response can be seen as the peaks at stimulating frequencies.

In order to avoid mutual influences between stimulating frequencies, the following additional restrictions for each group of four simultaneously flickering LEDs were applied during the randomization of the 16 frequencies: $f_i \neq [f_j + f_k]/2$, $f_i \neq 2f_j - f_k$, $f_i \neq 2f_k - f_j$. It is important to mention that in the second part of the experiment subjects were instructed to focus their gaze at the middle of the LED's array, but attenting on all four LEDs. The stimulation times were chosen in the same way as in the first part of the experiment. The entire procedure took on average about 40 minutes per subject including subject EEG preparation.

2.4 Evaluation methods

Classical two dimensional control that operates with SSVEP requires five classes: Four classes are dedicated to the directions (up, down, left and right) and one class for selection of actions. During the calibration process, the goal is to determine the five stimulating frequencies that achieve best SSVEP responses. In order to prove that the calibration procedure outputs the same five best frequencies with the strongest SSVEP responses, the standard chain calibration and the novel calibration method with four flickering LEDs at once were compared. We distinguish two ways for estimating the calibration quality and to evaluate its impact: The conventional fast Fourier transform (FFT) and the Minimum Energy Combination (MEC) method [2].

2.4.1 Discrete Fourier Transform

Fourier analysis is a powerful tool in signal analysis that can be applied to detect SSVEP peaks. The analysis signal is the EEG signal recorded from the i-th electrode when visual stimulation is applied $y_i(t)$. The Fourier theorem states that any function in the time domain can be expressed in the frequency domain as the sum of sinusoidal functions with different frequencies:

$$y(t) = \sum_{j=1}^{N} A_n \sin(2\pi f_n t + \Phi_n). \tag{1}$$

The discrete Fourier transform of the signal $y_i(t)$ at electrode i sampled at discrete times t_n is given by:

$$F(f_n) = \frac{1}{N} \sum_{n=1}^{N} y(t_n) \varepsilon^{j2\pi f_n}. \tag{2}$$

2.4.2 Minimum Energy Combination

To extract discriminant features, the signals from the i electrodes need to be combined. This can be achieved by defining a channel vector s of length N_t which is a linear combination of the electrode signals, y_i

$$s = \sum_{i=1}^{N_y} w_i y_i = Yw, \tag{3}$$

where w is a vector of weights $[w_1, \ldots, w_{N_y}]$ associated with the individual electrode signals. The aim of the channel s is to enhance the information contained in the EEG while reducing the nuisance signals. Several channels can be created by using different sets of weights, depending on the nature of the SSVEP signal and the noise. Equation (3) can be generalized for N_s channels as

$$S = YW \tag{4}$$

with the set of channels $S = [s_1, \ldots, s_{N_s}]$ and the corresponding weight matrix $W = [w_1, \ldots, w_{Ns}]$.

First, orthogonal projection is used to remove any potential SSVEP activity from the recorded signal,

$$\tilde{Y} = Y - X(X^T X)^{-1} X^T Y. \tag{5}$$

The remaining signal $\tilde{Y}$ contains approximately only noise, artifacts and background activity.

In the next step the weight vector $\hat{w}$ which minimizes the energy of the signal $\tilde{Y}$ is found by optimizing

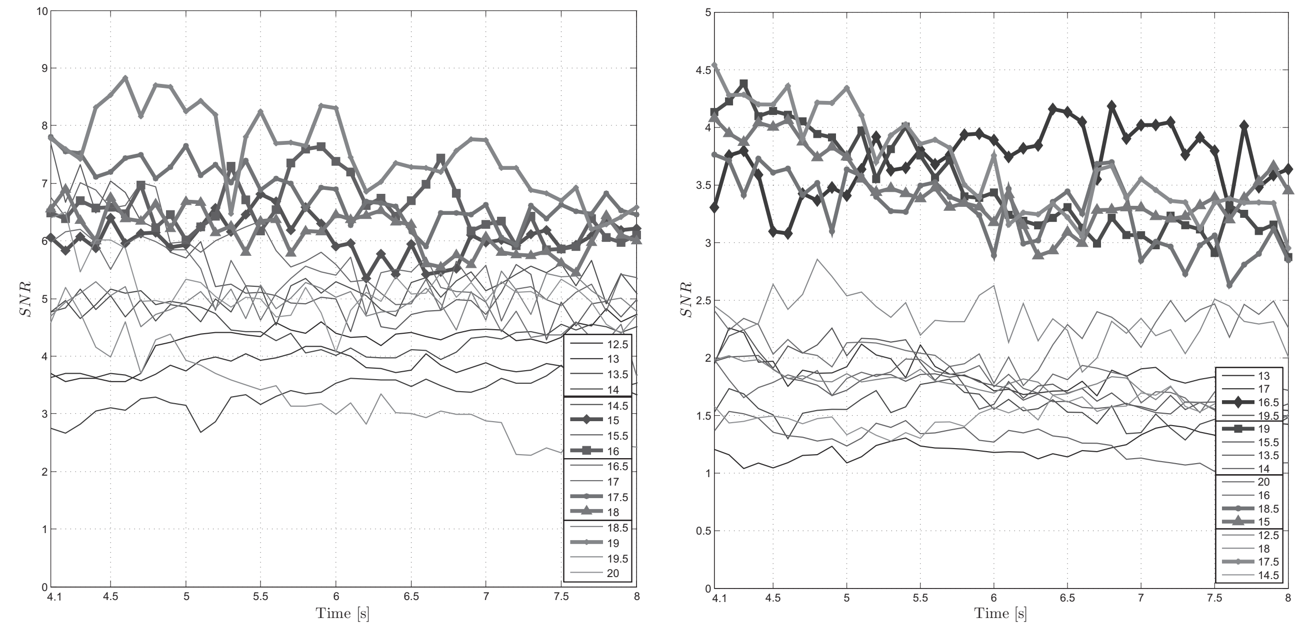
$$\min_{\hat{w}} \left\| \tilde{Y}\hat{w} \right\|^2 = \min_{\hat{w}} \hat{w}^T \tilde{Y}^T \tilde{Y} \hat{w}. \tag{6}$$

Vector w will minimize the component of the noise and nuisance signal in the corresponding channel signal (equation (3)). The weight matrix can be chosen based on the eigenvalues in ascending order $(\lambda_1, \lambda_2, \ldots)$ and the corresponding eigenvectors $(v_1, v_2, \ldots)$

$$W = \left[\frac{v_1}{\sqrt{\lambda_1}} \cdots \frac{v_{N_s}}{\sqrt{\lambda_{N_s}}} \right]. \tag{7}$$

The total number of channels used, N_s, is selected by finding the smallest value for N_s which satisfies

$$\frac{\sum_{i=1}^{N_s} \lambda_i}{\sum_{j=1}^{N_y} \lambda_j} > 0.1 \tag{8}$$



(a) SNRs for individually presented stimuli

(b) SNRs for stimulation in groups of 4 LEDs

Figure 4: SNR distributions for two different stimuli presentations for Subject 4 (a) during visual stimulation with 16 individual flickering frequencies ranged from 12.5 to 20 Hz (steps of 0.5 Hz) and (b) during stimulation in groups of 4 LEDs. The five stimulating frequencies with the strongest SNRs are plotted with a thick line. SNR values were calculated on the basis of the time segment length of 4 *s* every 100 *ms* using Minimum Energy Combination method as described above and six EEG channels ($P_Z, PO_3, PO_4, O_Z, O_9, O_{10}$).

This can be interpreted as selecting the number of channels in such a way as to discard as close to 90% of the nuisance signal energy as possible [2].

The estimated SSVEP signal to noise ratio over all channels N_s and all corresponding harmonics N_h is given by

$$\hat{T} = \frac{1}{N_s N_h} \sum_{l=1}^{N_s} \sum_{k=1}^{N_h} \frac{\hat{P}_{k,l}}{\hat{\sigma}_{k,l}^2}. \tag{9}$$

Here, $\hat{P}_{k,l}$ denotes the estimated SSVEP power at the kth harmonic frequency in the channel signal s_l,

$$\hat{P}_{k,l} = \|X_k^T s_l\|^2 , \tag{10}$$

and $\hat{\sigma}_{k,l}^2$ is the corresponding estimated noise level which represents the power in the kth harmonic frequency in the channel signal s_l if no SSVEP response were present. An auto-regressive $AR(p)$ model of order $p = 4$ is fitted to each modified channel signal,

$$\tilde{s}_l = \tilde{Y} w_l \tag{11}$$

using a Levinson-Durbin recursion. The resulting model parameters and the estimated white noise variance driving the auto-regressive process are then used to predict the noise level at the kth harmonic SSVEP frequency.

Using the methodology outlined above, the estimated signal to noise ratio of the EEG signal acquired over a segment length T_s with respect to one of the stimulation frequencies f_i can be denoted as $\hat{T}(f_i), i = 1 \ldots N_f$. In the present setup, only the first harmonic of the stimulating frequency was taken into consideration, N_h = 2, and the time segment length T_s of 4 s was used.

3. RESULTS

Results obtained from two calibration runs for five subjects are summarized in Table 1. Selected frequencies are shown when stimuli were presented in sequence order and for multi-target stimulation (four LEDs flickering with the different frequencies). Fourier Analysis were performed for single frequencies and results are shown in column 1. For direct comparison, column 2 shows results for Fourier analysis and column 3 for Minimum Energy Combination when stimuli are presented in groups of four frequencies. Fig. 1 shows the results of two representative subjects obtained during chain stimulation with 16 flickering frequencies. Fig. 1a shows results for subject 3 considered to be a good SSVEP performing subject and Fig. 1b for subject 5 considered less performing. Fig. 3 shows the results obtained for the same subjects with stimulation groups of four stimulation frequencies. The same data was analyzed with the Minimum Energy Combination algorithm to find the best five stimulation frequencies. Fig. 4 presents the SNR distributions for subject 4: Fig. 4a for individually presented stimuli and Fig. 4b for the stimulation in groups of 4 LEDs.

4. DISCUSSION

Two calibration methods were compared: single LED and multi-target group LED stimuli. For both methods, we computed the frequency spectrum (FFT) of single EEG signal at electrode PO_4 (see section 2.4.1). The length of the time window used for FFT-analysis was 21 seconds (offset of 1 s). From the results, it can be observed that for both calibration methods (single and multi-target) the visual stimula-

Table 1: Results over 5 subjects. Table presents five frequencies [Hz] with the largest SSVEP responses for individual stimulation vs. stimuli presented in groups of 4 LEDs, bold marked values represent equal selected frequencies for FFT and SNR.

Subject	Single LED FFT	Group LED FFT	Group LED SNR
1	14.5, 12.5, 20.0, 16.5, 17.0	**12.5**, **13.5**, **20.0**, 17.0, 19.5	**12.5**, **13.5**, 14.0, **20.0**, 16.0
2	15.5, 16.5, 20.0, 19.5, 17.0	**15.5**, 16.5, **19.5**, **17.0**, **17.5**	**15.5**, **17.0**, **17.5**, 16.0, **19.5**
3	13.0, 17.0, 16.5, 15.0, 18.0	**16.5**, **13.0**, 14.5, **19.0**, **18.0**	17.0, **16.5**, **13.0**, 19.5, **19.0**
4	15.0, 19.0, 17.5 18.0, 13.5	**15.0**, **19.0**, **17.5**, 13.5, **18.5**	16.5, **17.5**, **15.0**, **19.0**, **18.5**
5	17.5, 14.0, 19.0, 20.0, 19.5	20.0, **19.5**, 15.0, 19.0, 17.0	16.5, 17.5, **19.5**, 18.0, 16.0

tion leads to an increase of the SSVEP response at the corresponding frequency (see Fig. 1 and 3). The spectral amplitude of the SSVEP response vary significantly between the subjects and different stimulation frequencies. Based on the maximal values, we chose five best frequencies for all subjects as shown in Table 1. A high correlation of the best frequencies determined by two calibration methods was found. At least three of five frequencies encountered by two calibration ways were the same. This approach allows us to shorten the total duration of calibration time from 464 seconds ($16 \times 23 + 16 \times 6 = 464$, 16 frequencies, 23 seconds is the mean duration of stimulation and 6 seconds is the mean resting time) to 116 seconds ($4 \times 23 + 4 \times 6 = 116$, four groups a four frequencies).

Another way to compare the two calibration approaches is the calculation of SNR values using Minimum Energy Combination method as explained in section 2.4.2. In comparison to the FFT-analyses with window length of 21 seconds the SNR method returns the adequate outcomes from data sets recorded during 9 seconds (offset of 1 s). This brings an additional advantage in terms of the performance of calibration. The criterion for the selection of five best frequencies is based on the calculation of the integral value of the SNR distribution over the time. In column *Group LED SNR* (Table 1) the five best frequencies for each subject are displayed. The SNR-based calibration provides similar five best frequencies to the FFT-analysis based calibration. For four subjects at least three of five frequencies matched. Only for the subject 5, whose responses were very low compared with other subjects, one frequency of five frequencies matches over all methods.

5. CONCLUSION

In this paper a novel calibration method for SSVEP based Brain-Computer Interfaces was presented. We have showed that using multi-target stimulation, the calibration time is decreased without reducing the quality of the SSVEP responses. The Minimum Energy Combination algorithm was useful to determine frequency responses when stimuli are presented simultaneously (the same procedure as during an online BCI experiment).

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