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ADAPTIVE PARAMETER SETTING IN A CODE MODULATED VISUAL EVOKED POTENTIALS BCI

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ABSTRACT: Code-modulated visual evoked potentials (c-VEPs) BCI are designed for high-speed communication. The setting of stimulus parameters is fundamental for this type of BCI, because stimulus parameters have an influence on the performance of the system. In this work we design a c-VEP BCI for word spelling, in which it is possible to find the optimal stimulus presentation rate per each subject thanks to an adaptive setting parameter phase. This phase takes place at the beginning of each session and allows to define the stimulus parameters that are used during the spelling phase. The different stimuli are modulated by a binary m-sequence circular-shifted by a different time lag and a template matching method is applied for the target detection. We acquired data from 4 subjects in two sessions. The results obtained for the offline spelling show the variability between subjects and therefore the importance of subject-dependent adaptation of c-VEP BCI.

INTRODUCTION

Among the BCIs based on electroencephalographic signals (EEG), a VEP BCI allows for spelling from a keyboard of flashing characters, by identifying the target character, which the user is gazing at. Depending on the specific stimulus modulation design used, current VEP based BCIs can be distinguished into BCI systems using frequency modulated VEP (f-VEP), time modulated VEP (t-VEP) and BCI systems using pseudo-random code-modulated VEP (c-VEP) [1]. In a c-VEP BCI, all characters flash according to a predefined pseudo-random sequence, as a m-sequence [2], circular-shifted by a character-dependent time lag. For a given character, the m-sequence evokes a VEP in the EEG of the subject [3], which can be used as a template. This template is obtained during a calibration phase at the beginning of each session. A c-VEP BCI can potentially achieve a very high-speed communication level, reaching an average information transfer rate (ITR) of 108 ± 12 bit/min [3]. The stimulus modulation is crucial to build a high performance c-VEP BCI. Many studies investigate the effect of stimulus specificity on the target flashing modulation, applying different pseudo-random sequences [4], with different bit length sequences [5]. Isaksen et al. proved that among different types of code none provided a superior performance, showing that the "optimal-code" depends on the subject [4]. Wei et al. [5] explored different stimuli layout parameters such as the size, color and proximity of the stimuli, different length sequences and different lags between adjacent stimuli, providing the best set of parameters to increase the performance in a multi-target c-VEP BCI. Aminaka et al. propose a green-blue stimulus compared with the classical black-white [6], showing that the chromatic green–blue stimulus can give high result of accuracy, but not always better than the black-white color combination. Nazamfar et al. [7] explored different color stimulation: black and white, red and green and blue and yellow, stimulation sequence with three different bit lengths of 31, 63 and 127 bits but also three different bit presentation rates of 30, 60 and 110 bps. They showed that it is possible to find a compromise between high decision rate and subject comfort, using a m-sequence of 63-bit, a presentation rate of 60 bps and red-green for stimulus color. The stimulus presentation rate is another important parameter that can influence the system performance. The most common value used for coding sequence is 60 Hz. Wittevrongel et al. [8] proposed a study in which they compare the traditional flashing pattern frequency of 60 Hz to a faster one at 120 Hz. Applying a novel decoding algorithm based on spatio-temporal beamforming, they showed that with a faster stimulation is possible to increase the performance of the system, reaching a ITR of 172.87 bits/min. Analyzing these studies is clear that it is not possible to define an universal optimal stimulus parameter setting suitable for each BCI user. In order to obtain a BCI system with high speed communication that respects the subject's comfort is necessary to develop a system adaptable to the subject. In our study we developed a subject-dependent system with four different stimulus presentation rates of 15 Hz, 20 Hz, 30 Hz and 60 Hz. The objective is to find the optimal presentation frequency to obtain a pleasant stimulus per each subject. We demonstrate that the decreasing of the stimulation frequency does not imply the decreasing of the system performance showing the importance of the BCI-user adaptation.

MATERIALS AND METHODS

Adaptive parameter setting phase:

In a traditional c-VEP BCI with a refresh rate of 60 Hz and target encoded by binary sequence, each element

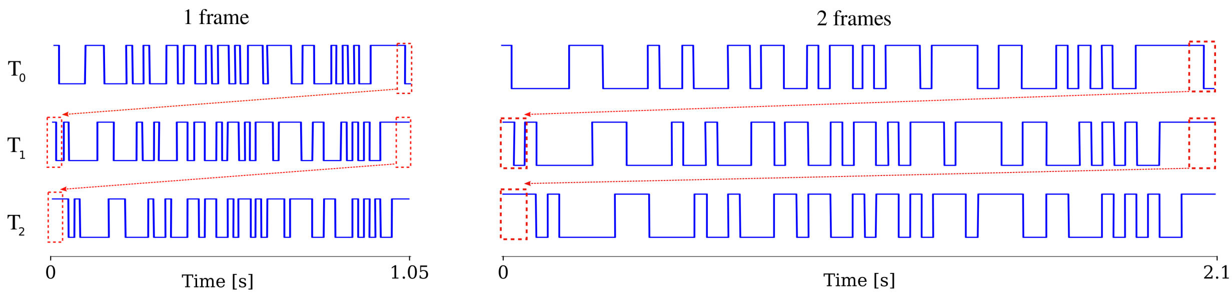

Figure 1: Illustration of the circular-shift process for the stimulus sequence for the first 3 targets. On the left, the stimulus sequences have a frame rate of 60 Hz (1 frame) and on the right, a frame rate of 30 Hz (2 frames). The figure shows the stimulation sequence for the target T_0, for the target T_1, circularly shifted with a time lag τ_s with respect to T_0 and for the target T_2, circularly shifted with a time lag τ_s with respect to T_1. The red dash boxes indicate the time lag τ_s corresponding to the # frames, listed in Tab. 1.

Table 1: Stimulus parameters set for each two consecutive targets in the adaptive parameter setting phase. The time lag $\tau_s = (2\ bits/60\ Hz) \cdot \#frames$. The length of one sequence t_s is computed as $t_s = (63\ bits/60\ Hz) \cdot \#frames$. The flashing duration of each target is $t_k = t_s \cdot \#stimulus\ cycles$

target1-target2	# frames	# stimulus cycles	τ_s	t_s	t_k
A - D	1	10	0.033s	1.05 s	10.50 s
A - P	2	8	0.067s	2.10 s	16.80 s
T - I	3	5	0.10s	3.15 s	15.75 s
V - E	4	4	0.13s	4.20 s	16.80 s

of the sequence is flashed on the screen for a time $t_b = 16.67\ ms$, corresponding to the duration of one frame. We developed a system in which the targets are encoded by a 63-bit m-sequence, but each element of this sequence can be flashed for 1, 2, 3 or 4 frames. On a 60-Hz screen, the characters on the virtual keyboard will thus flash at 60 Hz, 30 Hz, 20 Hz or 15 Hz. In this way it is possible to flash the target faster or slower and to find the stimulus pattern most adapted to each subject, while maintaining a system with high performance. Our protocol thus starts with an adaptive parameter setting phase. In this phase the subject has to focus on the targets of a word of eight characters, shown in Fig. 2, so the word can be divided in four pairs of targets and each pair follows the setting reported in Tab. 1. The flashing rate is thus changed every two targets. We compare the correlation between all the VEP responses recorded for each stimulus cycle of the two targets flashed with the same frame value per each channel c, to detect at which stimulus setting the evoked response of the subject is most prominent. Let ρ_1^c be the averaged correlation of the VEP responses over the N stimulus cycles of the target 1, ρ_2^c the averaged correlation of the VEP responses over the N stimulus cycles of the target 2 and ρ_{12}^c the averaged cross-correlation between the N stimulus cycles of the VEP response of the target 1 and the VEP response of the target 2. Based on the fact that when the user is gazing at a target, the specific VEP recorded in the EEG should be the same for each stimulus cycle of the same target, the expectation is a high value for ρ_1^c and ρ_2^c and a low value for ρ_{12}^c. The score λ^c evaluates the difference between the autocorrelation ρ_1^c and the cross-correlation ρ_{12}^c per channel for each parameters setting. The λ^c score is computed following equation (1), where std_1^c is the standard deviation of the VEP responses over the N stimulus cycles of the target 1 and std_{12}^c is the standard deviation of the VEP responses over the N stimulus cycles of the target 1 and target 2.

$$\lambda^c = \frac{\rho_1^c - \rho_{12}^c}{std_1^c + std_{12}^c} \tag{1}$$

At the end of the data acquisition of this adaptive phase the score λ per each set of parameters is averaged over the three best channels, for which ρ_1^c is the highest. The largest score λ is chosen to select the best stimulation number of frame.

Experimental setup:
The BCI software consists of OpenViBE [9] for signal acquisition, and a custom keyboard-display control software which we developed in C++. This software is run on a Windows 7 computer with an Intel(R) Xeon(R) processor. Two different LCD monitors are used: one (DELL U2711) is used during the acquisition to monitor the EEG signal quality, and the other (DELL 2709W) is set at 60 Hz with a resolution of 1920x1080 with a NVIDIA Quadro FX 580 graphic card and it is used for the stimuli presentation on a virtual keyboard. The keyboard, displayed in Fig. 2, is a 4x8 matrix containing 32 characters: letters sorted alphabetically from A to Z followed by backspace, symbols "?", "!", "." and numbers 1 and 2. Each character is placed in a circle with a dark grey background. Below the matrix of targets a text field shows the characters of the word that the subject has to gaze at. Each character of the virtual keyboard flashes according a binary sequence composed of 0 and 1. If the bit in the corresponding binary stimulation sequence is 1 the character flickers in light grey, if it is 0 in black, as illustrated in Fig. 2. The color combination light grey/black was chosen instead of white/black, in order to make the contrast more comfortable for the subjects. The stimuli are

synchronized with the refresh rate of the monitor and a trigger signal is provided by a TCP network connection to synchronize the stimulus presentation and the EEG data recordings.

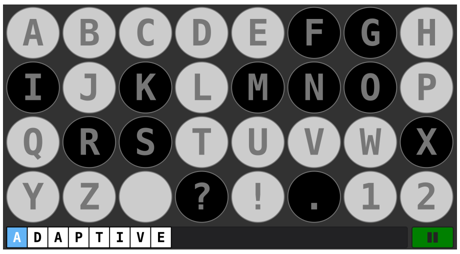

Figure 2: Virtual keyboard. During the stimulation the target is highlighted in blue below the keyboard.

Participants and data acquisition:
Four healthy volunteers (one male, average age 35, std 5 years) participated in the c-VEP BCI experiment. The experiment took place in our premises at Inria and was approved by the Operational Committee for the assessment of Legal and Ethical risks of the institute. All subjects had normal or correct to normal vision and did not suffer from epilepsy or other nervous diseases. Each subject took part in two identical sessions, half a week apart one from the other, and all of them completed the whole experiment. All the subjects were c-VEP BCI-naive participants. During the experiment, each subject was seated in a comfortable armchair 100 cm away from the computer monitor placed in a quiet room. During each session the EEG signal of the subject was recorded from ANT-Waveguard cap and a Refa8 amplifier (512 Hz sampling rate). To set the impedance between the electrodes and the subject's skin below 10 KΩ, a conductive gel was applied to the ground (FPz) and to the 12 electrodes placed in positions *Fz*, *F3*, *F4*, *Cz*, *C3*, *C4*, *Pz*, *P7*, *P8*, *Oz*, *O1*, *O2*. Each session consisted in 2 phases: the adaptive setting phase and a second phase in which the subject focuses on imposed characters, in which each target flashes according to the set of parameters found during the adaptive phase. To avoid the effect of fatigue on the experiment, the subject was allowed to take a rest of 5 minutes between the two phases. Each session lasted around 45-60 minutes, including the time for the experiment preparation (positioning of the cap and conductive gel injection) and the time for the data acquisition. During the adaptive setting phase a word of eight characters is displayed on the screen, below the keyboard. The characters are flashed following a 63-bit m-sequence and its time shifted version by 2 bits [3], an example for the circular shift of the stimulus sequence can be seen in Fig. 1. The stimulus parameters, in terms of number of frames and number stimulus cycles, follow the set of stimuli parameters reported in Tab. 1. Each target, before starting the stimulation, is highlighted in blue in the virtual keyboard to indicate to the subject the target position in the virtual keyboard. This adaptive setting phase lasts around 2 minutes. At the end of this phase the data collected is processed, as explained in the subsection *Adaptive parameter setting phase*, and the output of the processing gives the best set of parameters per subject for that session. Moreover the subject was asked for which value of frame rate the visual stimulus was more comfortable. Then, during the second phase, the subject has to focus his/her attention on the characters of a specific word written below the keyboard. In this phase each target is highlighted in blue before starting to flash and then all the characters flash following the set of best parameters computed during the first phase. Each subject has to spell five different words (42 characters in total and 10 targets), with a pause of one minute between each word.

Offline processing:
The EEG data $\mathbf{X}$ collected with N stimulus cycles on c channels, are bandpass filtered between 4 and 22 Hz with a Butterworth filter of order 4. The canonical correlation analysis (CCA) [10] is applied as spatial filter to improve the signal-to-noise ratio of the EEG signal. The objective of CCA is to find the two transformations W_X and W_S which maximize the correlation between the raw EEG-data $\mathbf{X}$ and the desired VEP waveform $\mathbf{S}$ [11].

$$CCA(X,S) = \max_{W_X W_S} \frac{W_X^T \mathbf{X}\mathbf{S}^T W_S}{\sqrt{W_X^T \mathbf{X}\mathbf{X}^T W_X} \cdot \sqrt{W_S^T \mathbf{S}\mathbf{S}^T W_S}} \quad (2)$$

To compute $\mathbf{S}$ we average over the number of stimulus cycles N the responses recorded for the first character of the first word that the subject has to gaze during the second phase, we consider only the three best channels c_b selected during the adaptive setting phase and then replicate N times the signal to obtain $\mathbf{S}$ [11], in this way $\mathbf{X}$ and $\mathbf{S}$ have the same number of stimulus cycles N. Then W_X is multiplied with $\mathbf{X}$ to compute the spatially filtered signal x. For target identification the method of template matching [3] is used. The reference template T_0 is calculated by averaging the signal x of the first character of the first word over the N stimulus cycles. The templates of all others targets T_k ($k = 0,...,31$) are generated by circularly shifting the template T_0. The duration t_s of the template and the time lag τ_s between two consecutive targets depends on the number of frames set for each subject, as listed in Tab. 1. To detect the attended target we compute a cumulative correlation per target. We segment the spatially filtered signal in epochs starting at the 'start' trigger, sent at the beginning of each stimulus cycles, and lasting the length of a stimulation sequence, specific to each subject (see Tab. 3), in order to obtain the epochs x_n, with $n = 0,...,N$. To set the N stimulus cycles, the cumulative correlation between the stimulus repetitions is computed and an arbitrary threshold is fixed at 0.8, considering the normalized correlation of each subject. Finally we compute the cumulative correlation coefficient ρ_k between each template T_k and the epochs x_n, following the equation 3.

$$\rho_k = \sum_{n=0}^{N} \frac{T_k \cdot x_n}{\sqrt{T_k \cdot T_k} \cdot \sqrt{x_n \cdot x_n}} \quad (3)$$

Table 2: Average λ score with standard deviation and the frame rate preferred by the subject during the adaptive parameter setting phase. In bold the maximum λ score corresponding to the frame rate selected at the end of the adaptive parameter setting phase.

	subject	1 frame	2 frames	3 frames	4 frames	subject preference
Session1	S1	0.25 ± 0.05	**0.86±0.08**	0.69 ± 0.09	0.45 ± 0.03	no preference
	S2	1.23 ± 0.12	**1.83±0.32**	1.60 ± 0.18	1.53 ± 0.08	2 frames
	S3	0.43 ± 0.14	**0.71±0.06**	0.51 ± 0.03	0.34 ± 0.05	2 frames
	S4	0.51 ± 0.20	0.61 ± 0.08	**0.93±0.15**	0.72 ± 0.00	3 frames
Session2	S1	0.32 ± 0.05	**0.88±0.08**	0.80 ± 0.09	0.36 ± 0.3	no preference
	S2	0.56 ± 0.20	1.72 ± 0.13	0.91 ± 0.12	**2.41±0.24**	4 frames
	S3	0.20 ± 0.04	0.84 ± 0.05	0.54 ± 0.17	**0.91±0.08**	4 frames
	S4	0.63 ± 0.09	**0.76±0.05**	0.56 ± 0.08	0.38 ± 0.05	2 frames

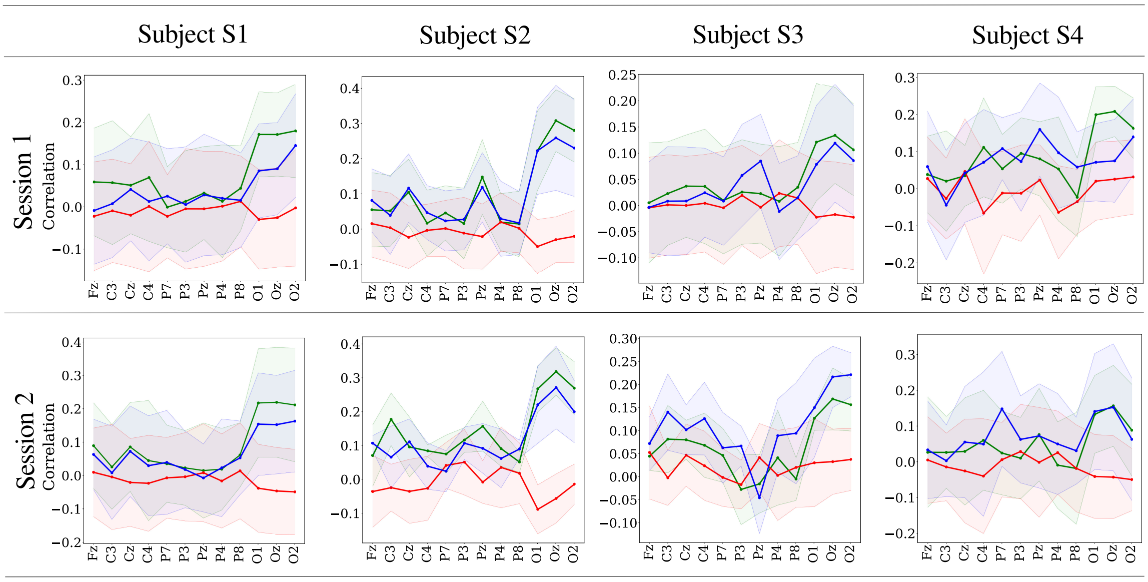

Figure 3: Correlation curves of the optimal number of frames, listed in Tab. 3, obtained for each subject at the end of session 1 and session 2. The average auto-correlation per channel ρ_1 in green and the average auto-correlation ρ_2 per channel in blue. The average cross-correlation $\rho 12$ is represented in red.

The target k with the largest coefficient ρ_k is detected as the attended target k_a. The offline spelling accuracy of each word is computed to evaluate the performance of the BCI system. Basically, if the detected target k_a corresponds to the target k at which the subject is gazing at, then the right character is detected. The number of correctly detected characters is computed for each word that the subject has to spell during the second phase. Finally the accuracy per word is computed as the proportion of correctly detected characters.

RESULTS

Tab. 2 lists the λ scores obtained per subject and session as well as the frequency rate preferred by the subject. We can observe that only for the subject S1, who did not express a preference, the optimal frame rate is unchanged between the two sessions. For the other subjects the optimal number of frames changes between one session and the other. For the subject S2 the largest λ obtained at the end of the first session is 1.83 ± 0.32 corresponding to 2 frames. If we compare this result with respect to the results obtained at the end of the second session, we can notice that for the same number of frames the λ value is 1.72 ± 0.13, but the largest λ value is reached for 4 frames, with a value equal to 2.41 ± 0.24. The same trend can be observed for the other subjects, except subject S4. Fig. 3 shows the auto-correlation and cross-correlation curves obtained for each subject for the best frame rate selected at the end of the adaptive setting parameter phase. The parameters obtained at the end of the adaptive setting phase and set for the second phase are listed in Tab. 3. In Fig. 4 we show the averaged offline spelling accuracy, over the five words, of each subject for each session. The accuracy of subject S2 reaches a good level, 80% $\pm$ 15% in the second session and over 74% $\pm$ 12% in the first one. We can notice that for three subjects there is an increase of performance during the second session, that proves the performance improvement of the subject over several sessions. The accuracy of the subject S3 achieves 43% $\pm$ 18% during the second session, compared to 11% during the first session. Instead, for the subject S4, the performance during the first session, reaching 56% $\pm$ 12% of accuracy, is better than the one of the second session, with an accuracy of 33% $\pm$ 8%.

Table 3: Summary of the adaptive stimuli parameter setting. Number of frames, number of stimulus cycles and stimulus duration of the target (t_k) per subject and per session.

	subject	# frames	# stimulus cycles	t_k		subject	# frames	# stimulus cycles	t_k
Session 1	S1	2	7	14.7 s	Session 2	S1	2	7	14.7 s
	S2	2	7	14.7 s		S2	4	3	12.6 s
	S3	2	6	12.6 s		S3	4	3	12.6 s
	S4	3	4	12.6 s		S4	2	6	12.6 s

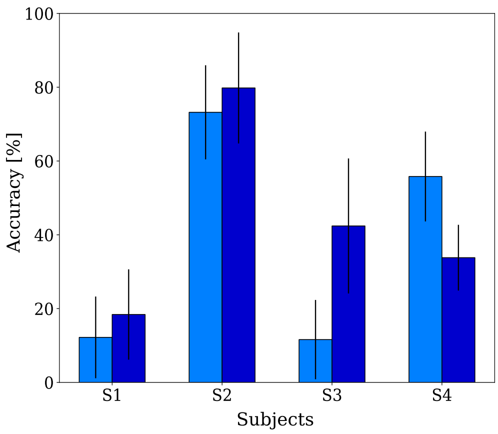

Figure 4: The box plots report the averaged accuracy over five words obtained in the offline spelling for each subject and each session. The session 1 is represented in light blue, session 2 in blue. The error bar represents the standard deviation.

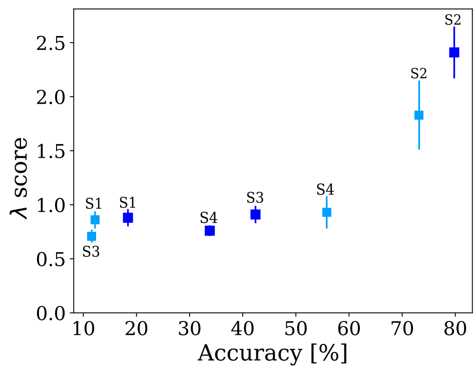

Figure 5: The best λ scores, in bold in Tab. 2, of each subject with respect to the offline spelling accuracy, showed in Fig. 4. The session 1 is represented in light blue, session 2 in blue. The error bar represents the standard deviation. The λ score increases according to the accuracy.

DISCUSSION

In our study we explored the influence of frequency stimulation on the VEP responses by the development of an adaptive setting phase. At the end of this adaptive phase we compute the λ score that can be considered as a performance estimator for a c-VEP BCI system. Indeed if we compare the largest λ value with respect to the accuracy values reached in the offline spelling, shown in Fig. 5, we can notice that a largest λ value corresponds to higher accuracy value per subject. The obtained results show an important variability, both inter-subject and intra-subject. Indeed one of the challenges of using BCIs over extended periods of time is the variation of the user's performance from a session to another. There are many factors that can influence the BCI user's performance between different sessions, for example distraction, visual fatigue, loss of concentration, motivation [12]. All these factors should be considered to build an high performance BCI. Moreover we demonstrate that decreasing the flashing pattern frequency, the length of a stimulus cycle increases, but it can be compensated by setting a lower number of stimulus cycles. As illustrated in Tab. 3, the flashing duration of each target is not longer even when the frame rate is longer than one frame, which is the most common value of frame rate used in c-VEP systems. This means that the stimulus duration at different frame rates does not impact the performance of the system. Our method does not require a long calibration phase as, for example, other c-VEP BCI in which the number of stimulus cycles is around 200 for the reference target [3, 5] in the calibration phase. During the spelling phase some systems obtain high value of spelling accuracy with only 2 stimulus cycles [3] and others with 40 stimulus cycles [5]. In these systems they reached very high level of spelling accuracy, but in our case we aim to develop a method that can reach high value of accuracy, as we obtain for the subject S2, replacing the traditional calibration with a shorter adaptive setting phase and finding a compromise on the number of stimulus cycles during the spelling phase. The objective is to obtain a system in which is possible to define the more pleasant stimulus for each subject, in order to increase the performance of the system. Tab. 2 proves that the most comfortable frame rate expressed by the subject is also the one for which the performance is the highest. This can explain why a subject that performs well for a frequency rate performed less well for another frequency rate during the same session, demonstrating the need for an adaptive system. It would certainly be interesting to understand why some subjects reach a higher accuracy value and others do not, achieving a mean accuracy lower with respect to other c-VEP BCI systems [3, 11]. Among many reasons that can explain this difference, there is the quality of the signal recorded during the experiments. Fig. 6 shows the spatially filtered responses for participants with the worst and the best performance in session 2, in term of accuracy (subject S1 and subject S2 respectively). Observing the VEP responses in Fig. 6 is evident that there is a repeatability of the VEP response for the subject S2, for

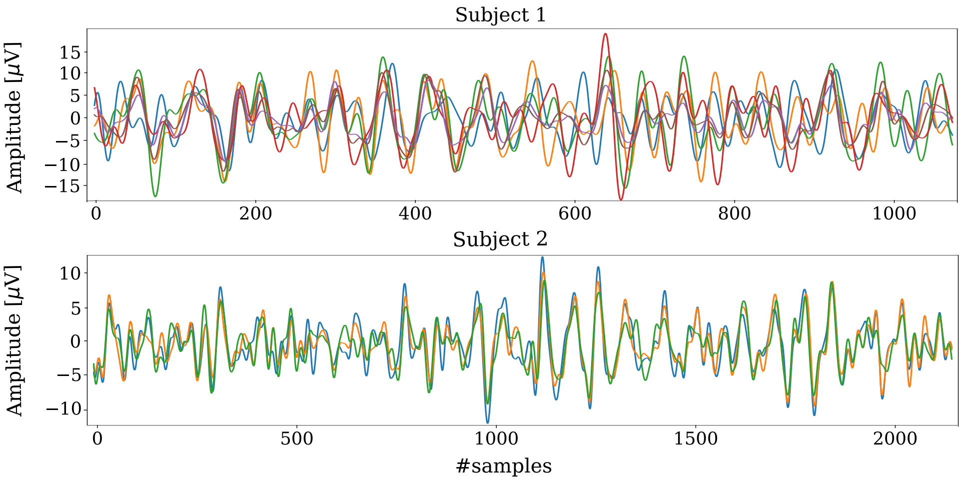

Figure 6: The spatially filtered VEP responses recorded at each stimulus cycle overlapped for target k, acquired during session 2 for subject S1 and subject S2, respectively the subjects that perform worst and best.

whom the accuracy is around 80% and a large variability on the responses for the subject S1, who obtains an accuracy of around 20%. This lack of repeatability can be due to the inexperience of the subject or also by external noise. Future work will be focused on the inclusion of other variables in the adaptive setting parameter phase, such as the selection of the stimulus sequence, color stimulus and development of an online early stopping method to find the optimal number of stimulus cycles per subject. Finally, to further improve our system, the next step will be to identify the disturbance factors and find methods to remove them in the VEP responses, by different applications of spatial filters, or by modelling the VEP response and the external disturbances and noise.

CONCLUSION

In a c-VEP BCI, the stimulus strategy applied to flash the target is fundamental to obtain a high performing BCI. In this work we parametrized the stimulus modulation with four different stimulus presentation rates. We developed an experimental protocol that deploys a preliminary phase to define the optimal setting of stimulation frequency to tackle the problem of variability inter-subject and intra-subject. Optimally, these results would help with the design of a subject-dependent c-VEP BCI with high communication performance.

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