DETECTION OF HIGH FREQUENCY STEADY STATE VISUAL EVOKED POTENTIALS FOR BRAIN-COMPUTER INTERFACES

G. Garcia Molina, D. Ibañez, V. Mihajlović, D. Chestakov

Philips Research Europe
High Tech Campus 34, 5656AE, Eindhoven, Netherlands
email: {gary.garcia, david.soria, dmitri.chestakov, vojkan.mihajlovic}@philips.com

ABSTRACT

Brain-computer interfaces (BCI) based on steady-state-visual-evoked-potentials (SSVEP) offer higher information throughput and require shorter calibration periods than other BCI modalities. SSVEPs are oscillatory responses elicited by oscillatory visual stimuli (e.g. using flickering LEDs) that can be detected in the electroencephalogram (EEG). The SSVEP is more prominent in occipital sites and consists of oscillatory components matching that of the stimulus and/or its harmonics. The electrode sites for optimal SSVEP detection change with the frequency of the stimulus. The emphasis here is on SSVEPs elicited by high-frequency stimuli ($>$30 Hz) because they are minimally perceptible and prevent safety hazards linked to photo-induced epileptic seizures. Linear combinations of EEG signals (spatial filters) are used to construct signals exhibiting large SSVEP components. As in most applications relying on biosignals, individual specificity needs to be taken into account. Thus, the spatial filters need to be customized for each BCI user through a (preferably short) calibration procedure. In this study, we present an approach to automatically obtain the optimum spatial filters to detect the SSVEP at a given stimulation frequency. Our experiments on six subjects resulted on detection rates characterized by values of the area-under-the-ROC ranging from 0.8 to 1 for stimulation frequencies in the 30-45 Hz range.

1. INTRODUCTION

During the last two decades, Brain-computer interfaces (BCIs) have been emerging as plausible alternatives for offering communication and control to physically challenged people. Yet, the idea of achieving control through direct brain-activity monitoring appeals to a wider user group. Availability, lower cost, and convenience make the electroencephalogram (EEG) the preferred choice in brain monitoring for BCI applications [1]. The EEG is typically recorded using an array of electrodes positioned according to the 10-20 standard [2] (Figure 1a).

Three main electrophysiological sources of control are presently used in BCI research [1], namely motor imagery, the P300 potential, and the steady-state-visual-evoked-potential (SSVEP). The latter offers higher information throughput and require shorter calibration periods [3], making it more suitable for a practical implementation.

The SSVEP is an oscillatory component in the EEG that appears as a response to an oscillatory visual stimulus (OVS). The OVS can be rendered by various means including flickering lights or pattern reversal boards on a screen [4]. The SSVEP contains important components at the frequency of the OVS and harmonics.

SSVEP based BCIs operate by presenting the subject with a set of oscillatory visual stimuli at different frequencies. The SSVEP corresponding to the OVS on which the subject focuses his/her attention can be detected on the ongoing EEG. Each OVS is associated with an action which is executed by the system when the corresponding SSVEP is detected.

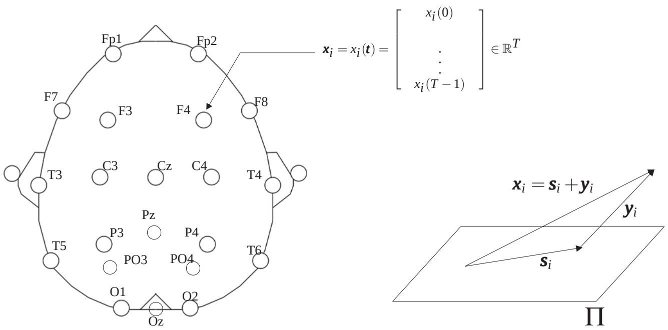
In BCI applications, SSVEPs are usually evoked by stimulation frequencies in the 7-30 Hz range [3, 5, 6] because the detection is more reliable given the relatively large SSVEP amplitude. However, to limit the annoyance and to prevent safety risks linked to photoepilepsy [7, 8], our experiments focus on stimulation frequencies higher than 30 Hz where the SSVEP detection poses more difficulties [9].

Detection of the SSVEP mainly relies on estimating the power of occipital signals (electrodes O1, O2, or Oz, see Figure 1) at the stimulation frequency and higher harmonics. Indeed, the SSVEP is more prominent at occipital sites because of their proximity to the primary visual cortex. However, depending on the subject's cognitive state the SSVEP can also be stronger at other sites including frontal ones [10]. In addition, despite of being called "steady", the SSVEP amplitude can be modulated by several user related factors including attention, fatigue, and eye movements [4]. Consequently reliable SSVEP detection requires taking into account the signals at several electrodes as well as the mentioned user factors.

The approach in [5] determines an optimum linear combination (spatial filtering) of the signal at various electrodes by maximizing the ratio of the power of SSVEP related activity to that of non-SSVEP related activity. This approach results in a reliable metric to detect the SSVEP at a certain stimulation frequency. The optimum spatial filter and an estimate of the noise power at the frequencies of interest is determined for each EEG epoch that is analyzed. Performing such estimates in a per-epoch basis does however hamper real-time operation especially if a large number of electrodes are recorded.

In this paper, we follow the approach in [5] to implement a BCI system with high stimulation frequencies. This implies that only the first harmonic is relevant which allows us to obtain a more accurate estimate of the power of the SSVEP related activity (see Eq. 4). In addition, by means of a training phase, we take into account the subject's attention to optimize the spatial filtering and overcome the real-time limitations of [5].

This paper is organized as follows. Section 2 presents the basic model of the SSVEP and its detection is described in Section 3. In Section 4 the experimental validation of our approach is discussed. The conclusions and directions for



(a) (b)

Figure 1: (a) Standard 10-20 EEG electrode positioning. (b) Vector interpretation of the recorded signals and the space Π of SSVEP components.

future work are presented in Section 5.

2. SSVEP MODEL

A signal recorded at a particular electrode location, that contains T samples can be seen as a vector in $\mathbb{R}^T$. Because of this interpretation, we use hereafter the terms vector and signal without explicit distinction.

The signal $\boldsymbol{x}_i$ (where i indexes the electrode location) recorded while the subject observes an OVS at a frequency f can be written as a sum of the SSVEP component (denoted as $\boldsymbol{s}_i$), background EEG, and noise [5]. For convenience the background EEG and the noise at electrode i are combined into a single term denoted as $\boldsymbol{y}_i$. Thus, the following relation holds (see also Figure 1b).

$$\begin{aligned} \boldsymbol{x}_i &= \boldsymbol{s}_i + \boldsymbol{y}_i \\ &= \sum_{h=1}^{H} \left(a_{h,i} \sin(2\pi h f \boldsymbol{t}) + b_{h,i} \cos(2\pi h f \boldsymbol{t}) \right) + \boldsymbol{y}_i, \end{aligned} \tag{1}$$

where the SSVEP component is modeled as a linear combination of vectors in the set:
$\Phi = \{\sin(2\pi h f \boldsymbol{t}), \cos(2\pi h f \boldsymbol{t}) \,|\, h = 1, \ldots, H\}$,
$\boldsymbol{t} = [0, \ldots, T-1]'$ is a vector of sample indices, H is the number of harmonics that are considered in the model, and $a_{h,i}, b_{h,i}$ are real numbers.

Equation 1 can be generalized to the whole set of electrodes $\{\boldsymbol{x}_i \,|\, i = 1, \ldots, N\}$ (N being the number of electrodes) in the following matrix form:

$$X = SA + Y, \tag{2}$$

where the matrix[1] $X \in \mathbb{M}^{T \times N}$ has as columns the vectors $\boldsymbol{x}_i$, $Y \in \mathbb{M}^{T \times N}$ has as columns the vectors $\boldsymbol{y}_i$, $S \in \mathbb{M}^{T \times 2H}$ has as columns the vectors in the set Φ, and $A \in \mathbb{M}^{2H \times N}$ is the matrix of linear combination coefficients such that $A_{h,i} = a_{h,i}$ if h is odd and $A_{h,i} = b_{h,i}$ if h is even. By means of the coefficients $a_{h,i}$ and $b_{h,i}$, the model in (2) takes into account the differences of SSVEP-strength across the scalp.

[1]The notation $\mathbb{M}^{m \times n}$ refers to the space of real matrices having m rows and n columns

3. SSVEP DETECTION

The objective of SSVEP detection in a BCI application is to determine the strength to which an OVS at a frequency f elicits an SSVEP in an EEG epoch $X \in \mathbb{M}^{T \times N}$.

From the recorded epoch X and S only, one has no access to the elements of A in (2). Thus, to determine the SSVEP strength and influence on different electrode locations, a signal $\boldsymbol{x}_w$ is constructed such that: $\boldsymbol{x}_w = \sum_i w_i \boldsymbol{x}_i = X\boldsymbol{w}$, where $\boldsymbol{w} = [w_1, \ldots, w_N]'$. The power of the SSVEP in $X\boldsymbol{w}$ (denoted as $P(X\boldsymbol{w}, f)$) can be estimated as the sum of the modulus of the discrete Fourier transform at frequencies $f, 2f, \ldots, Hf$ divided by the number of samples T. This yields:

$$\begin{aligned} P(X\boldsymbol{w}, f) &= \frac{1}{T} \sum_{h=1}^{H} (sin(2\pi f h \boldsymbol{t}') X\boldsymbol{w})^2 \\ &\quad + \frac{1}{T} \sum_{h=1}^{H} (cos(2\pi f h \boldsymbol{t}') X\boldsymbol{w})^2 \\ P(X\boldsymbol{w}, f) &= \boldsymbol{w}' X' M X \boldsymbol{w}, \end{aligned} \tag{3}$$

where:
$M = \frac{1}{T} \sum_{h=1}^{H} sin(2\pi h f \boldsymbol{t}) sin(2\pi f \boldsymbol{t}') + cos(2\pi h f \boldsymbol{t}) cos(2\pi f \boldsymbol{t}')$.

The signal $\boldsymbol{x}_w$ can be considered to be the result of a spatial filter (e.g. across the electrodes) with coefficients $\{w_i\}$ applied to the measured signals $\boldsymbol{x}_i$. Such spatial filter is determined in such a way that the ratio of $X\boldsymbol{w}$'s power associated with the SSVEP activity to that associated with non-SSVEP activity is maximum. Such ratio can be determined by relying on the geometric interpretation in Section 3.1.

3.1 Construction of the spatial filter $\boldsymbol{w}$

The linearly independent vectors in the set Φ generate a vector-space (Π) in $\mathbb{R}^T$ of dimension $2H$ (Figure 1b). In this paper's framework, we assume Π to be the space where the SSVEP components lie. Thus, Π's orthogonal complement $\Pi^\perp$ contains the non-SSVEP components.

Since the vectors in Φ are linearly independent, the projection matrix P on Π can be written as $P = S(S'S)^{-1}S'$ [11]. The component of $X\boldsymbol{w}$ in $\Pi^\perp$ is equal to $X\boldsymbol{w} - PX\boldsymbol{w}$. The Euclidean norm of the latter: $\|(X - PX)\boldsymbol{w}\|^2$ divided by T represents the power of the non-SSVEP related activity.

The power of the SSVEP related activity in $X\boldsymbol{w}$ can be approximated by $\boldsymbol{w}'X'MX\boldsymbol{w}$ (see Eq. 3). This approximation is postulated notwithstanding the fact that the background EEG and noise can have, in general, components at the stimulation frequency and its harmonics (i.e $PY \neq 0$).

The spatial filter $\boldsymbol{w}$ corresponds to the argument that maximizes the ratio $\rho = \frac{\boldsymbol{w}'X'MX\boldsymbol{w}}{\|(X-PX)\boldsymbol{w}\|^2}$. This is conveniently expressed in (4).

$$\boldsymbol{w} = \arg\max_{\tilde{\boldsymbol{w}}} \frac{\tilde{\boldsymbol{w}}' X' M X \tilde{\boldsymbol{w}}}{\tilde{\boldsymbol{w}}'(X - PX)'(X - PX)\tilde{\boldsymbol{w}}}. \tag{4}$$

The ratio in (4) is a *generalized Rayleigh quotient* [12] whose maximum can be found through a generalized eigendecomposition of the matrices $X'MX$ and $(X - PX)'(X - PX)$. This results in two matrices $W, \Lambda \in \mathbb{M}^{N \times N}$ such that:

$$X'MXW = (X - PX)'(X - PX)W\Lambda, \tag{5}$$

where Λ is a diagonal matrix whose diagonal contains the eigenvalues which, by construction, are larger than 1 [13].

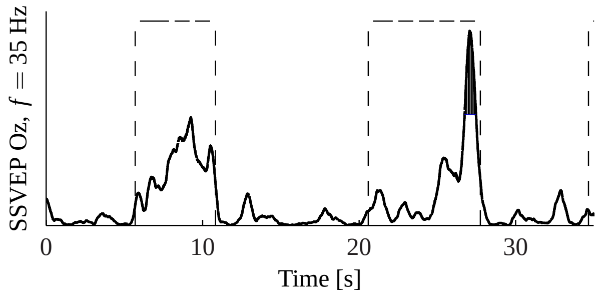


Figure 2: SSVEP variation at electrode Oz. The dashed lines indicate the periods where the OVS is presented. The shadowed area indicates the time segment where the training epoch is selected.

The corresponding eigenvectors are in the columns of W. The largest element in Λ corresponds to the maximum of the quotient in (4). The column of W corresponding to such maximum is the sought spatial filter $\boldsymbol{w}$.

3.2 Training phase to determine $\boldsymbol{w}$

To obtain the optimum spatial filtering using (4), an appropriate EEG epoch X has to be selected. This selection results from a brief training phase in which the subject is presented with an OVS at the targeted frequency f while the corresponding EEG is recorded.

The SSVEP variation across time is first estimated by applying a 2Hz-narrow band filter (peak filter) centered around f to the signal from electrode Oz, squaring the resulting signal, and finally applying a moving-average filter to obtain an estimate of the instantaneous signal power. An example of the resulting signal is depicted in Figure 2 where the regions limited by the dashed lines correspond to the periods where the OVS was presented. The SSVEP gradually increases from the moment the stimulation begins but its power changes depending on the subject's state.

A T-sample long quasi-stationary epoch is selected from the signal recorded during the training phase. This is accomplished by identifying the maximum SSVEP power in the signal of Figure 2 and selecting T samples around it (the limits of the darkened region in Figure 2 illustrate this procedure). These sample indices permit to determine X. Applying (4) yields the optimum $\boldsymbol{w}$. The matrix M in (4) results from (3) when $H = 1$. The latter is due to the fact that high frequency oscillatory visual stimuli are considered and consequently the stimuli harmonics are not relevant.

4. EXPERIMENTAL VALIDATION

Six subjects S1 to S6 (one female) aged 23, 25, 25, 30, 29, and 28 respectively participated in six recording sessions that lasted for about one hour (including EEG-cap setup). Oscillatory visual stimuli where presented at 30, 35, 40, and 45 Hz which were rendered using a flickering LED through a diffusing panel in order to have a uniform shining spot. The shining spot had 7.5 cm diameter and subjects were seated at an approximate distance of 50 cm from the shining spot. The current on the LED was modulated so as to obtain a sinusoidal luminance at the desired stimulation frequency.

The EEG was acquired using a BIOSEMI [14] amplifier with active electrodes at a sampling rate of 2048 Hz. The signals from 20 electrodes: Fp1, Fp2, F7, F3, F4, F8, T3, C3, C4, T4, T5, P3, Pz, P4, T6, PO3, PO4, O1, Oz, and O2 referenced to Cz were recorded (see Figure 1a). The OVS was jointly recorded with the EEG by means of a photodiode connected to the amplifier.

In each session two recordings per stimulation frequency were done. In each recording, *stimulation periods* of random duration from 3 to 5 seconds were followed by *non-stimulation periods* of random duration from 5 to 10 seconds. A total of 12 sequences of stimulation/non-stimulation periods were applied per recording. This resulted in 144 stimulation periods per frequency and per subject.

The stimulation periods containing ocular artifacts, particularly eye blinks, were manually discarded. Indeed, we observed that after an eye blink the SSVEP power attenuates (due to the short period in which the eyes are closed) and regains its strength after a brief period of time. Signal containing artifacts due to head movements were also discarded because they can induce large components at the stimulation frequencies. Table 4 reports the number of stimulation periods remaining after artifact rejection.

Table 1: Stimulation periods after artifact rejection

	Subject					
Frequency [Hz]	S1	S2	S3	S4	S5	S6
30	126	131	116	124	138	117
35	111	137	124	140	110	131
40	138	141	142	112	115	119
45	125	135	141	122	117	117

For each subject and stimulation frequency twelve spatial filters were determined corresponding to each recording in the six sessions. The training epoch in each recording had a duration of 0.5 seconds and was selected using the approach in Section 3.2. Figure 4 depicts the topographical map of the spatial filters obtained from the first recording of sessions one to six for subject S1 and stimulation frequency of 35 Hz. It is important to notice the small variation of $\boldsymbol{w}$ across sessions. The within-session variation (i.e. when $\boldsymbol{w}$ is calculated in different stimulation periods within the same session) is expected to be even smaller. Thus, the spatial filter does not need to be updated in a per-epoch basis but can be updated at the beginning of a session. It is also important to notice the small values of $\boldsymbol{w}$ on electrode locations outside the occipital area. Thus, the most significant coefficients correspond to regions near the primary visual cortex. Such result indicates that using optimum spatial filters is in agreement with physiology intuition.

In Figure 3 we show the effect of applying the optimum spatial filter determined on session one, first recording (Subject S1, $f = 35Hz$) to the second recording of that session. Figure 3a represents the SSVEP strength calculated on the second recording of the first session on electrode Oz (as in Figure 2) while Figure 3b depicts the SSVEP strength after applying the spatial filter. It is clear that the detection performance is considerably improved in Figure 3b.

In Figure 5 we report the average spatial filters (across sessions and recordings) for each subject and $f = 35Hz$. While the relevant coefficients are concentrated around the occipital area, there is a significant variability from subject to subject. This result indicates that the spatial filters need to

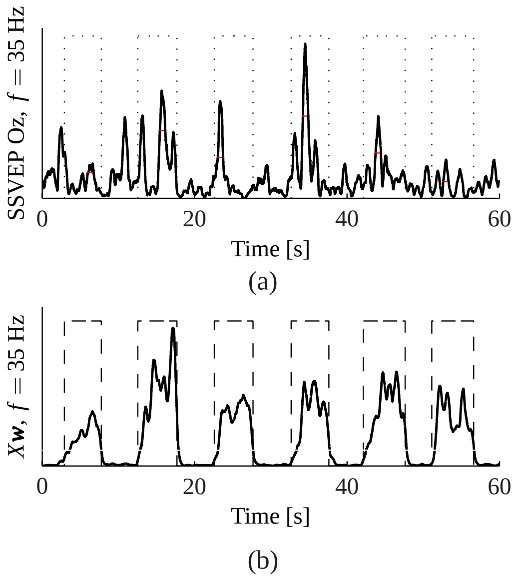


Figure 3: (a) SSVEP strength on the second recording of the first session calculated on electrode Oz (subject S1, $f = 35Hz$). (b) SSVEP strength after applying the optimum spatial filter determined on the first recording of the first session.

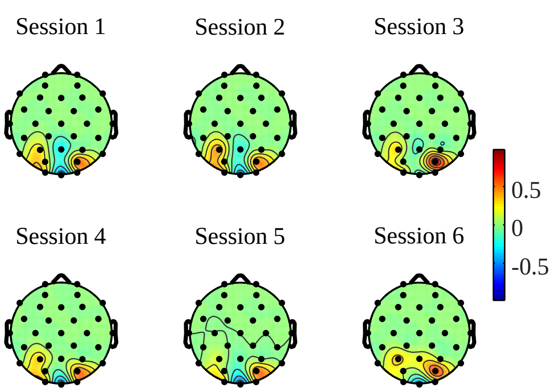


Figure 4: Variability of $\boldsymbol{w}$ across sessions (the norm of $\boldsymbol{w}$ was normalized to 1). Subject S1,
$f = 35Hz$. In the topographical map, the value of each coefficient of $\boldsymbol{w}$ is associated with a color (as indicated by the color-scale on the right) and reported at its corresponding location on the scalp.

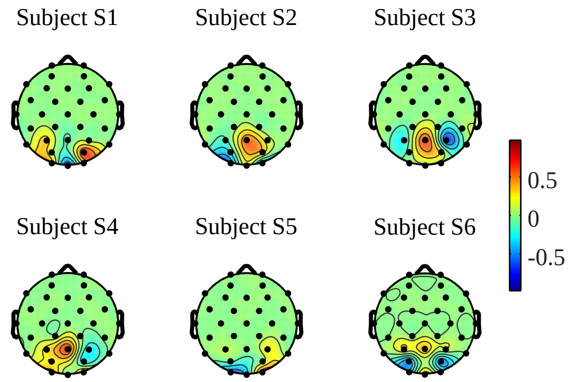


Figure 5: Variability of $\boldsymbol{w}$ across subjects (the norm of $\boldsymbol{w}$ was normalized to 1). Subjects S1 to S6, $f = 35Hz$.

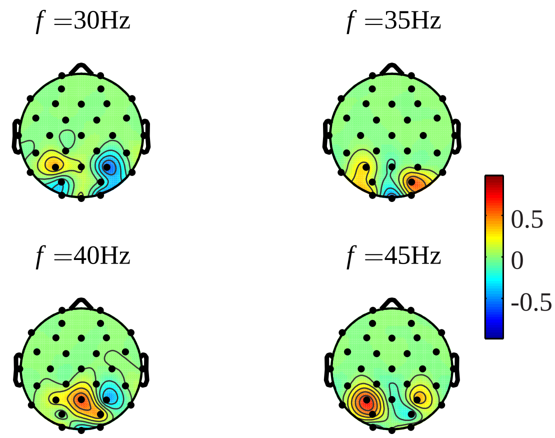


Figure 6: Variability of $\boldsymbol{w}$ across stimulation frequencies (the norm of $\boldsymbol{w}$ was normalized to 1). Subject S1.

be customized and that a minimum number of electrodes has to be used for taking into account the individual specificity. This is especially relevant for designing a consumer BCI.

In Figure 6 we report the variability of the spatial filters for the same subject (S1) across different frequencies. We can observe that not only customization is required but also the spatial filter optimization depends on the stimulation frequency. This result is supported by physiological evidence reporting the difference of SSVEP strength distribution across the scalp for different stimulation frequencies [10].

To assess the detection accuracy of the optimum spatial filter, we computed the receiving-operator characteristic (ROC) for each stimulation frequency and subject. For different values of a detection threshold (acting on the SSVEP strength), the ROC plots the true positive rate, which in this paper corresponds to those stimulation periods where the SSVEP could be correctly detected by applying the optimum spatial filter, versus the false positive rate which in this paper corresponds to those non-stimulation periods where an SSVEP was incorrectly detected. The area under the ROC provides an indication of the detection accuracy. The closer the area to one is, the more accurate the detection can be. Table 4 reports the average (across sessions and recordings) area under the ROC curve for the four stimulation frequencies and subjects S1 to S6. It is important to notice that for all subjects the stimulation frequency at 35 Hz provides particularly good results. This fact may be explained by a hypothesis that postulates resonance regime near 30 Hz [4]. As expected the detection accuracy degrades for high frequencies.

Table 2: Average area under ROC curve. Subjects S1 to S6 for each stimulation frequency

	Subject					
Frequency [Hz]	S1	S2	S3	S4	S5	S6
30	0.96	0.93	0.94	0.95	0.97	1.00
35	1.00	0.98	0.97	0.95	0.96	0.93
40	0.98	0.90	0.89	0.92	0.93	0.90
45	0.90	0.87	0.85	0.83	0.90	0.84

5. CONCLUSION AND FUTURE WORK

SSVEP based BCIs can offer higher throughput than other BCI modalities. However, to be viable as a consumer technology, they need to ensure a higher communication bit-rate and operate using high frequency (¿30Hz) visual stimulation in order to avoid annoyance and prevent safety hazards. Accurate detection of the SSVEP is crucial for achieving those improvements.

The optimum detection of the SSVEP can be accomplished by taking advantage of the multivariate information in the EEG. This is done by using a linear combination of the signals recorded at multiple EEG electrodes (spatial filter). The optimum spatial filter is results from optimizing the ratio between the power of SSVEP related components and that of non-SSVEP related components. Estimating such values can be done by taking into account that for high-frequency stimulation, higher harmonics are not relevant given the limited bandwidth of EEG.

Our results show excellent detection results in six subjects for four stimulation frequencies, namely 30, 35, 40, and 45 Hz. While there is a small variability of the spatial filter coefficients across sessions for a given subject and stimulation frequency, we observe a significant variability for different stimulation frequencies for a given subject. In addition, individual specificity of the spatial filter coefficients can also be observed. These results are of particular relevance for designing a practical BCI that can be used at home without expert assistance. Indeed, one should strive for customized and automated parameter optimization. The approach presented in this paper, constitutes an important advancement towards automatic BCI personalization.

The dynamics of the SSVEP and dependency on user factors are the object of numerous studies in theoretical neuroscience. The extent to which BCI operation modulates the SSVEP and allows the user to gain voluntary control over SSVEP amplitude is still in its infancy. Given our objective of bringing BCIs to consumers in the short term, we plan to incorporate additional user factors in the simple model in (2) to improve BCI operation and offer higher information transfer rates.

REFERENCES

[1] J.R. Wolpaw, N. Birbaumer, D.J. McFarland, G. Pfurtscheller, and T.M. Vaughan. Brain-computer interfaces for communication and control. *Clinical Neurophysiology*, 113:767–791, 2002.

[2] H.H. Jasper. The ten-twenty electrode system of the international federation. *Electroencephalography and Clinical Neurophysiology*, 10(1):371–375, 1958.

[3] M. Cheng, X. Gao, S. Gao, and D. Xu. Design and Implementation of a Brain-Computer Interface With High Transfer Rates. *IEEE Transactions on Biomedical Engineering*, 49(10):1181–1186, 2002.

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

[5] O. Friman, I. Volosyak, and A. Gräser. Multiple Channel Detection of Steady-State Visual Evoked Potentials for Brain-Computer Interfaces. *IEEE Transactions on Biomedical Engineering*, 54(4):742–750, 2007.

[6] S.P. Kelly, E.C. Lalor, R.B. Reilly, and J.J. Foxe. Visual Spatial Attention Tracking Using High-Density SSVEP Data for Independent Brain-Computer Communication. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 13(2):172–178, 2005.

[7] R. S. Fisher, G. Harding, G. Erba, G.L. Barkley, and A. Wilkins. Photic - and Pattern - induced Seizures: A Review for the Epilepsy Foundation of America Working Group. *Epilepsia*, 46(9):1426–1441, 2005.

[8] G. Garcia Molina. Detection of High-Frequency Steady State Visual Evoked Potentials Using Phase Rectified Reconstruction. In *16th European Signal Processing Conference EUSIPCO 2008*, 2008.

[9] M.A. Pastor, J. Artieda, J. Arbizu, M. Valencia, and J.C. Masdeu. Human cerebral activation during steady-state visual-evoked responses. *The Journal of Neuroscience*, 23(37):11621–11627, 2003.

[10] K.A. Ellis, R.B. Silberstein, and P.J. Nathan. Exploring the temporal dynamics of the spatial working memory n-back task using steady state visual evoked potentials (SSVEP). *NeuroImage*, 31:1741–1751, 2006.

[11] C. Meyer. *Matrix Analysis and Applied Linear Algebra Book and Solutions Manual*. SIAM, 2000.

[12] R.E. Prieto. A general solution to the maximization of the multidimensional generalized rayleigh quotient used in linear discriminant analysis for signal classification. In *Proceedings of the 2003 IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP 03)*, volume 6, pages 157–160, 2003.

[13] G. Sewell. *Computational Methods of Linear Algebra*. Pure and Applied Mathematics: A Wiley-Interscience Series of Texts, Monographs and Tracts, 2005.

[14] Biosemi. Biosemi system. http://www.biosemi.com.