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Classification of Steady-State Visual Evoked Potentials based on the Visual Stimuli Duty Cycle

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Abstract—The detection of Steady State Visual Evoked Potentials (SSVEP) in the electroencephalogram (EEG) allows creating non-invasive Brain-Computer Interface (BCI). To produce an SSVEP response, a visual stimulus must be presented to the user. This stimulus can be a light that flickers at a particular frequency. Classical SSVEP-BCIs consider a frequency for each BCI command. One problem for an SSVEP based BCI can be the number of simultaneous flickering stimuli. It is difficult to render many flashing boxes with as many frequencies as boxes, due to hardware constraint like the vertical refresh rate of a screen. As an alternative to the common paradigm that assigns one command to each frequency, we propose to classify different type of SSVEP responses based on the duty cycle of the flickering lights, the frequency being the same for evoking SSVEP responses. Three paradigms based on different duty cycles over six subjects are compared. The offline classification of the obtained SSVEP responses is performed with spatial filters combined with a Bayesian Linear Discriminant Analysis classifier. The results show that it is possible to efficiently discriminate SSVEP responses given by visual stimuli at the same frequency but with different duty cycles.

I. INTRODUCTION

Brain-Computer Interfaces based on non-invasive scalp electroencephalography (EEG) have emerged as an increasingly active multidisciplinary research area. Indeed, BCIs allow to communicate through direct neural activity measurements [1]–[3]. Different BCI paradigms have been proposed. They differ in the type of brain activity to detect. For creating an EEG-based BCI, brain responses such as event-related potentials, event-related desynchronization/synchronization (ERD/ERS), slow cortical potentials are commonly used. Several obstacles remain for proposing commercial BCIs. Among these obstacles, the low information transfer rate (ITR), which depends on the number of available commands and the classification rate, can be an issue for users with a high expectation in the BCI performance. For BCIs that require special external stimuli, *e.g.*, visual stimuli, their quality and their sources can be a bottleneck for increasing the number of basic commands in a BCI. As a full part of the BCI system, these stimuli shall be reliable, stable and should not involve any risk or inconvenience like visual fatigue for the user. When persons have to use a BCI daily, *e.g.* who

are unable to communicate through any classical ways, the ergonomic aspect can be as important as the ITR. As BCI applications are usually aimed for persons with severe disabilities, a BCI shall be convenient as much as possible [4]–[6].

In this paper, we focus on the detection of Steady State Visual Evoked Potentials (SSVEP) responses [7], [8]. SSVEP-BCIs are described as more accessible than other BCI systems. SSVEP-BCIs have been considered for several applications [9]–[11] and are described as reliable in the literature [12]–[14]. Compared to other BCI paradigms, they allow a high information transfer rate (ITR) and little or no user training [15]–[17]. However, BCIs based on SSVEP are not considered as independent BCIs as the generation of the VEP depends on the gaze control via extraocular muscles and particular nerves. For this SSVEP-BCI, the user shall be able to control his/her eye movements.

BCIs based on SSVEP use the response of the user attention to an oscillating visual stimulus. When a person is looking at one particular oscillating object, then its brain response can provide a way for tailoring a BCI. Usually, the stimuli that are used for inducing SSVEP responses are flickering lights at different frequencies. When an object flickers at a frequency f , then a response occurs in the visual cortex. This response corresponds to the frequency of the stimulus and its higher harmonics [18]. Therefore, it is possible to obtain different responses in relation to different frequencies. It is then possible to assign a command for each SSVEP response to create a BCI.

The amplitude and the phase that define an SSVEP response depend on three main parameters [19]:

- The frequency. The SSVEP responses with maximum amplitude are usually obtained in three frequency bands: 5-12Hz, 12-25Hz and 30-50Hz [20].
- The intensity of the flickering light.
- The structure of the repetitive visual pattern. This parameter is the focus of this paper, which deals with the stimulus duty cycle as the main parameter between SSVEP responses. The goal here is to determine if the duty cycle can be considered as a reliable parameter for the classification of SSVEP responses, *i.e.*, if it could be used as a parameter for evoking different kinds of

detectable SSVEP responses.

The paper is organized as follows: the different methods for spatial filtering and classification are first presented in the second section. Then, the experimental protocol is described in the third section. Finally, the results are presented and discussed in the last two sections.

II. METHODS

A. Signal structure

The signal for the stimuli depends on the hardware device [21]. Stimuli are usually presented on a set of LEDs or on an LCD screen. We consider the visual stimulation on a classical LCD screen with a vertical refresh rate of 60Hz. With visual stimuli on a monitor screen, the graphical user interface (GUI) of the BCI application and the stimuli can be on the same screen. When the visual stimuli and the application share the same screen, the subject does not need to shift his/her gaze too much between the stimuli and the GUI [16]. Monitors can also provide to the user different feedbacks, *e.g.* neurofeedbacks. The frequency power, the detection probability and other information can be displayed in real time near the visual stimuli for allowing both a better control of the user/patient and a control from the supervisor of the experiment. The repetitive visual pattern is composed of n frames with $n > 1$. Thus, the frequency of a stimulus based on n frames is $60/n$ Hz. A visual stimulus is represented on the screen by a flickering box (white/black).

The duty cycle D is defined by:

$$D = \frac{\tau}{T} \quad (1)$$

where τ is the duration when the function is non-zero, *i.e.* the number of black frames and T is the period of the function, *i.e.* the number of frames describing a period of the visual stimulus. Usually, the duty cycle of the repetitive signal is not mentioned in the literature for SSVEP experiments. In these cases, we can assume $D = 0.5$ when the information is not provided. The structure of the signal was specified in [22]. Kelly et al. consider two frequencies at 10.03Hz and 12.04Hz with duty cycles of 0.16 and 0.2, respectively. The impact of this choice on the overall performance was not measured.

B. Spatial filters

In an online BCI application, several types of SSVEP responses must be taken into account. Each type of SSVEP response corresponds to a particular frequency. In this multi-class classification problem, we consider N_f classes where each class corresponds to an SSVEP response, *i.e.* a particular frequency. We consider a visual stimulation with a flicker-frequency of f Hz is applied. We use the following description for the signal $y_i(t)$ as the voltage between the electrode i and a reference electrode at a time t :

$$y_i(t) = \sum_{k=1}^{N_h} a_{i,k} \sin(2\pi kft + \Phi_{i,k}) + B_{i,t} \quad (2)$$

where N_h is the number of considered harmonics h . The signal is decomposed into two parts: the SSVEP response and the noise. The first part corresponds to the evoked SSVEP response signal, which is composed of a number of sinusoids with frequencies in relation to the stimulus frequency and a number of N_h harmonic frequencies. Each sinusoid is therefore defined by its amplitude $a_{i,k}$ and its phase $\Phi_{i,k}$. The second part $B_{i,t}$ is dedicated to all the information that is not relevant to the SSVEP response.

The online detection of an SSVEP response on an EEG signal requires a time segment for the signal analysis. We consider a time segment of N_t samples of the signals, with a sampling frequency of F_s Hz.

$$y_i = Xa_i + B_i \quad (3)$$

where $y_i = [y_i(1), \dots, y_i(N_t)]^T$ contains the EEG signal for the electrode i in one time segment. The SSVEP information matrix X is of size $N_t \times 2N_h$. For N_y electrodes, the signal is defined as:

$$Y = XA + B \quad (4)$$

where $Y = [y_1, \dots, y_{N_y}]$ contains the sampled EEG signals from all the electrodes. A contains all the amplitudes for all the expected sinusoids for all electrode signals.

For enhancing discriminant features from the signal, the signals from the electrodes must be combined. A channel is used for a combination of the signals measured by different electrodes. A vector of channel data is denoted by s . Its purpose is to enhance the information contained in the EEG while reducing the nuisance signals. A channel signal is defined as a linear combination of y_i .

$$s = \sum_{i=1}^{N_y} w_i y_i = Yw \quad (5)$$

where w_i is the weight for the i^{th} electrode.

Several channels can be created by using several sets of weights w . We note N_s the number of channels. The channel creation is an essential step for enhancing the relevant signal [18], [23], [24]. For creating the channels, *i.e.* spatial filters, we consider the minimum energy combination, which is based on the principal component analysis (PCA) [14]. Its purpose is to have an optimal combination of the electrode signals, which cancels the nuisance signals as much as possible. The technique removes any potential discriminant components from all the electrode signals, by projecting them onto the orthogonal complement of the formal model of the signal X . It can generate a frequency power estimation of any frequency. Different sets of channels are created for each frequency. Thus, channels are set in relation to the expected frequency to observe. This method allows the combination of a fixed number of electrodes that minimizes the nuisance signals. The power of the expected frequencies and their harmonics are calculated for the N_s channels. For each frequency, the evaluation of the SSVEP response is defined by:

$$R = \frac{1}{N_s N_h} \sum_{i=1}^{N_s} \sum_{j=1}^{N_h} |P(i, j)| \quad (6)$$

where $|P(i, j)|$ is the amplitude of the frequency power in the channel i at the harmonic j . N_s , the number of channels, is equal to the number of electrodes. N_h is the number of considered harmonics. $N_h = 1$ is equivalent of using only the frequency of the visual stimulus. For the classification in the next sections, we set $N_h = 4$.

C. Classifiers

For the classification of SSVEP responses evoked by visual stimuli of the same frequencies but with different duty cycle, we consider the Bayesian linear discriminant analysis (BLDA) [25]. This classifier has been tested and successfully applied for the detection of P300 [26], [27]. This classifier finds a discriminant vector w such that the distance between the associated vector of a class c and $w^T p$ is minimized when the input vector p belongs to the class c . For this classifier we define the input vector p that contain frequency power at each harmonic:

$$p(j) = \sum_{i=1}^{N_s} |P(i, j)| \quad (7)$$

with $1 \leq j \leq N_h$. For this classifier, we consider a time segment of 2s for the analysis of the SSVEP response.

III. EXPERIMENTS

A. Materials

The EEG signal was recorded with sensors placed on the surface of the scalp via 8 standard passive (with no inbuilt circuitry) EEG electrodes; EEG are usually used for non-invasive BCIs. The locations of the electrodes are AF_Z for ground, C_Z for the reference and $PO_3, PO_4, P_Z, O_{10}, O_9, O_Z$ for the input electrodes [28]. The impedances below $5k\Omega$ were achieved by using an abrasive electrode gel. The EEG data were acquired with a G.tec amplifier [29], the sampling frequency was 128Hz. During the EEG acquisition, an analog bandpass filter between 2 and 35Hz, and a notch filter around 50Hz (main frequency in Europe) were applied directly inside the amplifier. For the stimuli display, an LCD screen of a laptop with the resolution of 1680×1050 pixels and a vertical refresh rate of 60Hz was used. The luminance is about $180.0cd/m^2$ with an estimated contrast of 280 : 1. The visual stimulus corresponds to a flickering square centered in the middle of the screen with a luminance equivalent to about $0.27cd$.

B. Subjects

Six healthy male subjects participated in this study. These subjects had no risk of epileptic seizure. They were all volunteers (unpaid) and belong to the same age group,

with an average age of 28.5 years and a standard deviation of 1.22 years. They are not BCI-naive subjects as they have all already tested some SSVEP-BCI systems.

C. Paradigms

Three paradigms were tested during the experiments. Each paradigm corresponds to a different duty cycle. For the first paradigm (A), the number of black frames is equal to the number of white frames in the repetitive visual stimulation. In the second and third paradigm, B and C, the number of black frames is equal to 2 and 1, respectively. Table I presents the signal structure for each paradigm and each frequency (1 for rendering a black box, 0 for white box).

The experimental protocol is the same for each paradigm. Each subject had to look during 20s at one particular stimulus. The task was to focus on the flickering box on the screen. The subjects were instructed to gaze at the flashing targets. If the subject was not focusing seriously on the screen, the session was restarted. The order of the trials was randomized. The lighting conditions and the subject position were identical for all experiments. For each frequency, six sessions were recorded. The subjects were sitting in a comfortable chair, wearing an EEG cap as described previously (cf. section III-A).

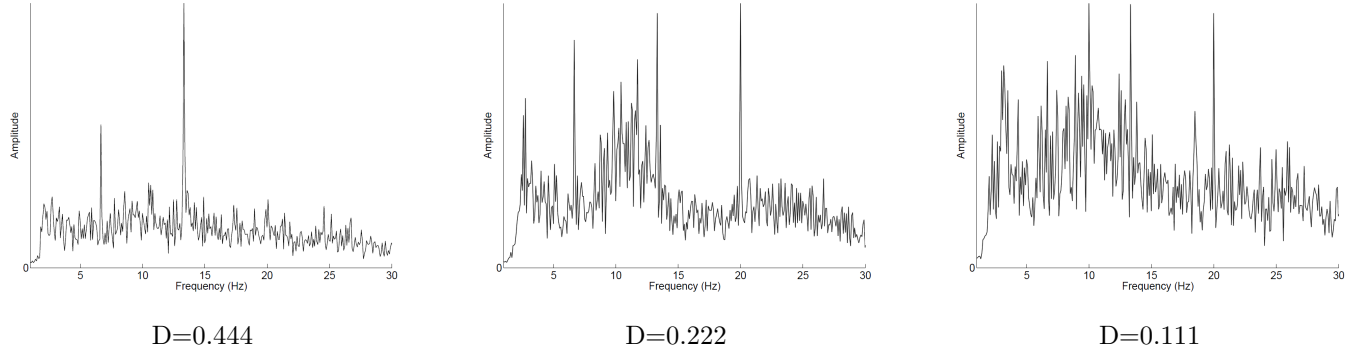
TABLE I
PARAMETERS FOR THE EACH PARADIGM.

Paradigm	Frequency (Hz)	D	Signal structure
A	6.66	0.444	111100000
	7.50	0.500	111100000
	8.57	0.429	11100000
B	6.66	0.222	110000000
	7.50	0.250	110000000
	8.57	0.286	11000000
C	6.66	0.111	100000000
	7.50	0.125	100000000
	8.57	0.143	10000000

IV. RESULTS

Figure 1 presents the amplitude of frequencies till 30Hz for Subject 2. For each paradigm, the amplitude was determined on a whole trial of 20s. In this case, the channel combination was achieved with a Laplacian filter. This figure highlights the interest for considering the amplitude at the different harmonics for determining the duty cycle of the visual stimulus. Indeed, the frequency of the visual stimulus (6.66Hz) and its first harmonic (13.33Hz) have high amplitude in the first paradigm. Furthermore, the first harmonic has higher amplitude than the fundamental frequency of the stimulus. In the second paradigm, the distribution of the amplitude is different: the second and third harmonics (20 and 26.66Hz) have clearly a peak. The SSVEP response seems more reliable in this paradigm. In the last paradigm, which has the lowest duty cycle, the amplitude of the first harmonic is very low compared to the others. The amplitude at 20Hz remains high and reliable

Fig. 1. Frequency amplitude during one trial of 20s for a stimulus at 6.66Hz for Subject 2.



for the detection. The low accuracy in the third paradigm can be explained by the low amplitude of the first harmonic and by consequence its low discriminant power in the detection. This harmonic can involve confusion in the detection. These distributions of the amplitude between the different harmonics are also observed for the two other frequencies.

The effect of the duty cycle on the SSVEP responses is evaluated thanks to the accuracy of their detection. The signal detection technique is applied on the signal every 100ms. The amplitude analysis suggested that the frequency power of the different harmonics could be discriminant for the classification of SSVEP responses evoked by the same frequency and different duty cycle. Table II presents the recognition rate of the binary classification of several SSVEP responses with different duty cycles. For this classification, 50% of the recorded EEG was used for training, the remaining data being used for the test. The goal is to determine if for a fixed frequency, it would be possible to classify different duty cycles. The duty cycle of paradigms B and C are relatively close. This small difference has an effect in the recognition rate with an average accuracy: 75.30%, 66.36% and 82.67% for the frequencies 6.66, 7.50 and 8.57Hz, respectively. When the difference of duty cycle is larger, like between paradigms A and C, the recognition is higher: 89.86%, 92.65% and 91.40% for the frequencies 6.66, 7.50 and 8.57Hz, respectively. With such high accuracies, the possibility to classify different SSVEP responses evoked by the same frequency appears as a promising tool for extending the number of possible commands in SSVEP-BCIs.

V. CONCLUSION

The visual stimuli on a common LCD screen can be an advantage for designing BCI graphical user interface, however it can be a drawback for enabling a large number of visual stimuli with different frequencies. The effect of the duty cycle, *i.e.* the structure of the periodic signal, of the visual stimuli has been tested and evaluated on the offline classification of SSVEP responses. Three duty

cycles and three flickering frequencies have been tested over six subjects. Only eight electrodes are used for recording the signal. The offline classification of the SSVEP responses has been successfully achieved with spatial filters combined with a Bayesian Linear Discriminant Analysis classifier. It is possible to discriminate SSVEP responses at the same frequency but with different duty cycles. It means that for a determined frequency, it is possible to observe different responses based on the difference of the signal structure. Using hardware with a limited number of available frequencies like LCD screens, the definition of several signal structures can extend the number of available BCI commands. First, the observed visual stimulus frequency should be detected. Then, the detection of its structure would allow determining the observed visual stimulus.

The results are based on a signal processing method that does not include the structure of the visual stimuli as a parameter. This strategy may have had an impact on the accuracy. To exploit the duty cycle effect across the SSVEP responses, the classifier should weigh the amplitude in relation to the particular subject's behavior. In addition to the signal processing part that might limit the outcome of the raw results, the LCD screen is one other relevant parameter. The quality of the stimuli (the response and the contrast of the screen) plays an important role in the accuracy. These encouraging results about the visual stimuli parameters suggest that there exist other ways than signal processing or user training for improving the quality of SSVEP-BCIs. Further works will deal with the evaluation of the proposed strategy in an online BCI with more subjects.

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TABLE II
 RECOGNITION RATE (IN %) OF THE BINARY CLASSIFICATION OF SEVERAL SSVEP RESPONSE WITH DIFFERENT DUTY CYCLE.

f (Hz)	Method	S1	S2	S3	S4	S5	S6	MEAN	S.D.
6.66	A vs C	72.58	94.20	94.80	95.16	93.91	88.53	89.86	8.81
	A vs B	74.19	88.89	99.64	93.36	87.27	95.87	89.87	8.91
	B vs C	52.33	63.44	80.10	83.87	83.15	88.89	75.30	14.22
7.50	A vs C	81.72	94.26	99.46	95.16	93.37	91.94	92.65	5.93
	A vs B	88.23	81.54	99.82	95.88	86.38	95.52	91.23	6.93
	B vs C	51.07	57.17	60.21	69.71	81.15	78.85	66.36	12.18
8.57	A vs C	81.90	87.27	98.92	87.10	94.98	98.21	91.40	6.95
	A vs B	71.86	63.80	88.35	71.14	66.13	89.25	75.09	11.05
	B vs C	60.21	86.56	93.55	81.36	84.40	89.96	82.67	11.80

REFERENCES

- [1] B. Z. Allison, E. W. Wolpaw, and J. R. Wolpaw, "Brain-computer interface systems: progress and prospects," *Expert Review of Medical Devices*, vol. 4, no. 4, pp. 463–474, 2007.
- [2] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan, "Brain-computer interfaces for communication and control," *Clin Neurophysiol*, vol. 113, pp. 767–791, 2002.
- [3] T. J. Sejnowski, G. Dornhege, J. d. R. Millán, T. Hinterberger, D. J. McFarland, and K.-R. Müller, *Toward Brain-Computer Interfacing (Neural Information Processing)*. The MIT Press, 2007.
- [4] N. Birbaumer, "Breaking the silence: Brain-computer-interfaces (BCI) for communication and motor control," *Psychophysiology*, vol. 43, pp. 517–532, 2006.
- [5] T. M. Vaughan, D. J. McFarland, G. Schalk, W. A. Sarnacki, D. J. Krusienski, E. W. Sellers, and J. R. Wolpaw, "The wadsworth BCI research and development program: At home with BCI," *IEEE Trans. on Neural Sys. and Rehabilitation Eng.*, vol. 14, no. 2, pp. 229–233, 2006.
- [6] F. Nijboer, E. W. Sellers, J. Mellinger, M. A. Jordan, T. Matuz, A. Furdea, S. Halder, U. Mochty, D. J. Krusienski, T. M. Vaughan, J. Wolpaw, N. Birbaumer, and A. Kübler, "A P300-based brain-computer interface for people with amyotrophic lateral sclerosis," *Clin Neurophysiol.*, vol. 119, no. 8, pp. 1909–1916, 2008.
- [7] F. Vialatte, M. Maurice, J. Dauwels, and A. Cichocki, "Steady-state visually evoked potentials: focus on essential paradigms and future perspectives," *Prog Neurobiol.*, vol. 90, no. 4, pp. 418–438, 2010.
- [8] Y. Wang, X. Gao, B. Hong, C. Jia, and S. K. Gao, "Brain-computer interfaces based on visual evoked potentials - feasibility of practical system designs," *IEEE Engineering in Medicine and Biology Magazine*, pp. 64–71, 2008.
- [9] E. C. Lalor, S. P. Kelly, C. Finucane, R. Burke, R. Smith, R. B. Reilly, and G. McDarby, "Steady-state VEP-based brain-computer interface control in an immersive 3d gaming environment," *EURASIP Journal on Applied Signal Processing*, vol. 19, pp. 3156–3164, 2006.
- [10] G. R. Müller-Putz and G. Pfurtscheller, "Control of an electrical prosthesis with an SSVEP-based BCI," *IEEE Trans Biomed Eng.*, vol. 55, pp. 361–362, 2008.
- [11] G. R. McMillan, G. L. Calhoun, M. S. Middendorf, J. H. Schnurer, D. F. Ingle, and V. T. Nasman, "Direct brain interface utilizing self-regulation of steady-state visual evoke response," *In Proc. of RESNA*, pp. 693–695, 1995.
- [12] H. Cecotti and A. Gräser, "Time delay neural network with Fourier Transform for multiple channel detection of steady-state visual evoked potential for brain-computer interfaces," *In Proc. of European Signal Processing Conference*, 2008.
- [13] X. R. Gao, D. F. Xu, M. Cheng, and S. K. Gao, "A BCI based environmental controller for the motion-disabled," *IEEE Trans. Rehab. Eng.*, vol. 11, no. 2, pp. 137–140, 2003.
- [14] O. Friman, I. Volosyak, and A. Gräser, "Multiple channel detection of steady-state visual evoked potentials for brain-computer interfaces," *IEEE Trans. Biomed. Eng.*, vol. 54, no. 4, pp. 742–750, 2007.
- [15] H. Cecotti, I. Volosyak, and A. Gräser, "Evaluation of an SSVEP based brain-computer interface on the command and application levels," *4th IEEE EMBS International Conference on Neural Engineering*, 2009.
- [16] H. Cecotti, "A self-paced and calibration-less SSVEP based brain-computer interface speller," *IEEE Trans. on Neural Systems and Rehab. Eng.*, vol. 18, pp. 127–133, 2010.
- [17] G. Bin, X. Gao, Z. Yan, B. Hong, and S. K. Gao, "An online multi-channel SSVEP-based brain-computer interface using a canonical correlation analysis method," *Journal of Neural Engineering*, vol. 6, 2009.
- [18] G. R. Müller-Putz, R. Scherer, C. Brauneis, and G. Pfurtscheller, "Steady-state visual evoked potential (SSVEP)-based communication: impact of harmonic frequency components," *Journal of Neural Engineering*, vol. 2, no. 1, pp. 123–130, 2005.
- [19] Z. Wu, Y. Lai, D. Wu, and D. Yao, "Stimulator selection in SSVEP-based BCI," *Int. Jour. Medical Engineering and Physics*, vol. 30, no. 8, pp. 1079–1088, 2008.
- [20] D. Regan, "Human brain electrophysiology: evoked potentials and evoked magnetic fields in science and medicine." *New York: Elsevier Pubs.*, 1989.
- [21] D. Zhu, J. Bieger, G. Garcia, and A. R. M., "A survey of stimulation methods used in SSVEP-based BCIs," *Computational Intelligence and Neuroscience*, vol. 2010, p. 12, 2010.
- [22] S. P. Kelly, E. C. Lalor, C. Finucane, G. McDarby, and R. B. Reilly, "Visual spatial attention control in an independent brain-computer interface," *IEEE Trans. Biomed. Eng.*, vol. 52, no. 9, pp. 1588–1596, 2005.
- [23] B. Blankertz, R. Tomioka, S. Lemm, M. Kawanabe, and K.-R. Müller, "Optimizing spatial filters for robust EEG single-trial analysis," *IEEE Signal Proc Magazine*, vol. 25, no. 1, pp. 41–56, 2008.
- [24] G. Burkitt, R. Silberstein, P. Cadush, and A. Wood, "Steady-state visual evoked potentials and travelling waves," *Clin. Neurophysiol.*, vol. 111, no. 2, pp. 246–258, 2000.
- [25] D. J. C. MacKay, "Bayesian interpolation," *Neural Comput.*, vol. 4, no. 3, pp. 415–447, 1992.
- [26] H. Cecotti, B. Rivet, M. Congedo, C. Jutten, O. Bertrand, E. Maby, and J. Mattout, "Suboptimal sensor subset evaluation in a p300 brain-computer interface," *Proc. of the 18th European Signal Processing Conference*, 2010.
- [27] U. Hoffmann, J. Vesin, K. Diserens, and T. Ebrahimi, "An efficient P300-based brain-computer interface for disabled subjects," *Journal of Neuroscience Methods*, vol. 167, no. 1, pp. 115–125, 2008.
- [28] G. E. Chatrian, E. Lettich, and P. L. Nelson, "Ten percent electrode system for topographic studies of spontaneous and evoked eeg activity," *Am J EEG Technol*, vol. 25, pp. 83–92, 1985.
- [29] *Guger Technologies* - <http://www.gtec.at/>.