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Optimal Spatial Filtering for the Steady State Visual Evoked Potential: BCI application

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***Abstract*—Focusing of attention on a repetitive visual stimulation (RVS) at a constant frequency, elicits the so called steady-state visual evoked potential (SSVEP). This effect can be advantageously utilized in brain-computer interfaces (BCIs). SSVEP based BCIs can offer higher bitrates and require shorter training time as compared to other BCI modalities. Detection of the SSVEP from the EEG can be facilitated through spatial filtering (linear combination of the signals recorded at several electrodes). Literature offers several options to perform this. In this paper we propose a taxonomy to categorize these methods and we extensively evaluate them using 22 stimulation frequencies. We suggest improvements to existing methods to increase the SSVEP detection performance. We also consider practical aspects in the discussion of results.**

I. INTRODUCTION

The steady state visual evoked potential (SSVEP) refers to the activity of the cerebral cortex that results from attending to a repetitive visual stimulus (RVS) oscillating at a constant *stimulation frequency*. The SSVEP can be observed in the scalp recorded electroencephalogram (EEG) as oscillatory components at the stimulation frequency and/or harmonics. The SSVEP is more prominent at parietal and occipital locations due to their relative proximity to the primary visual cortex [1].

The SSVEP is an effective neural source for EEG brain-computer interfacing (BCI). Indeed, compared to other BCI sources (e.g. motor imagery, P300, and slow cortical potentials), SSVEP based BCIs offer higher information transfer rates and require shorter calibration [2].

SSVEP based BCIs operate by presenting the user with a set of repetitive visual stimuli (RVSi) which have distinct properties from each other. Each RVS is univocally associated with a command/action that can be executed by the BCI. The user can select which action to execute by paying attention to the corresponding RVS because the SSVEP associated with such RVS is more prominent and can be detected from the EEG. For convenience, we use hereafter the term BCI to refer to an SSVEP based BCI.

In general, RVSi distinguish from each other by their stimulation frequency. However, phase and frequency/phase coding can also be used as distinguishing features [2], [3]. In any case reliable detection of the RVS which receives the user's focus of attention is crucial for successful BCI operation.

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Linear combination of the signals recorded at multiple EEG sites (this approach is usually refereed as to *spatial filtering*) constitutes a common approach to improve the SSVEP detection accuracy. The selection of the most appropriate spatial filter for SSVEP detection can be done through different approaches for EEG analysis including: simple average combination [4], principal component analysis [5], independent component analysis [6], common spatial patterns [7], and maximum contrast combination [4]. In this paper we assess several spatial filtering approaches in terms of their suitability for BCI, practical implementation, and physiological soundness. To this end we have performed extensive experiments using 22 different stimulation frequencies on three subjects.

This paper is organized as follows. The signal processing methods and the neurophysiological foundations that are used to obtain the spatial filters are summarized in Section II. The experimental protocols in this study are described in Section III. The results are presented and discussed in Section IV. Section V concludes this paper and suggests future research directions stemming from this work.

II. SIGNAL PROCESSING METHODS

In the SSVEP BCI framework, the goal of signal processing methods is to detect the presence of an SSVEP at a given stimulation frequency using the EEG.

In general, the problem consists in deciding if within a certain time window, the attention of the subject on an RVS has been sufficient to elicit an SSVEP. The EEG recorded in this time window is referred to as an *epoch* which, in terms of digital signal processing, can be written as a $T \times N$ matrix $\mathbf{X}$ having as columns the signals of the N recorded electrodes. The number of time samples in the epoch is noted as T.

The signal that results from applying a spatial filter $\mathbf{w}$ to $\mathbf{X}$ can be written as $\mathbf{x_w} = \mathbf{Xw} = \sum_{n=1}^{N} w_n \mathbf{x}_n$, where $\mathbf{x}_n$ is the n-th column (signal) of $\mathbf{X}$ and w_n is the n-th coefficient of the spatial filter.

A common preprocessing spatial filter is the so-called common average reference (CAR). CAR filtering (or derivation) consists in subtracting for each signal the average of all recorded signals. If the number of recorded signals is larger than about 16 and these are uniformly distributed on the head, the CAR derivation leads to a quasi-ideal EEG reference [8]. In the following, we assume that the signals are referenced to the CAR and further spatial filtering is applied on them. A single exception to this convention is in the average combination filter (second row in Table I).

In this paper's context, spatial filters are used to facilitate the detection of SSVEP. Literature proposes several approaches

TABLE I
SPATIAL FILTERING APPROACHES

Approach	Spatial filter coefficients	Hypotheses
Native (NAT)	$\begin{cases} w_n &= 1 \\ w_{m\neq n} &= 0 \end{cases}$ $n = \underset{1\leq n\leq N}{\operatorname{argmax}}\{\mathrm{AUC}(\mathbf{w})\}$	The SSVEP is highly localized in the vicinity of a single electrode. Usually an occipital or parietal one.
Average combination (AVG)	$w_n = \frac{1}{N}, \forall n$	The SSVEP manifests globally over the scalp without phase variations.
Best bipolar combination (BBC) [9]	$\begin{cases} w_{n<m} &= 1 \\ w_m &= -1 \\ w_{l\neq n,m} &= 0 \end{cases}$ $n, m = \underset{1\leq n,m\leq N}{\operatorname{argmax}}\{\mathrm{AUC}(\mathbf{w})\}$	The SSVEP is well localized and can maximally manifest if the signals at two distinct sites are combined with opposite phase.
Principal Component Analysis (PCA) [5]	$\mathbf{w} \;= \underset{\|\mathbf{w}\|^2=1}{\operatorname{argmax}}\{\mathbf{w}'\mathbf{C_X}\mathbf{w}\}$ $\mathbf{C_X} \;= E(\mathbf{X}'\mathbf{X})$ (cov. matrix) Out of the N principal components, we select the one that maximizes the AUC.	The SSVEP signal is uncorrelated from the background EEG.
Independent component analysis (ICA) [6]	$\mathbf{S} = \mathbf{XW}$ $\mathbf{W}$ is a $N\times N$ matrix whose columns are the spatial filters. The columns of S are sources mutually independent. Out of the N independent components, we select the one that maximizes the AUC.	The SSVEP signal is statistically independent from the background EEG.
Common spatial patterns (CSP) [7]	$\mathbf{w} = \underset{\mathbf{w}}{\operatorname{argmax}}\frac{\mathbf{w}'\mathbf{C_X}\mathbf{w}}{\mathbf{w}'\mathbf{C_X}\mathbf{w}+\mathbf{w}'\mathbf{C_Y}\mathbf{w}}$ $\mathbf{C_X}$ cov. matrix during RVS presentation (SSVEP signal). $\mathbf{C_Y}$ cov. matrix during RVS absence. This method requires the signals to be filtered using a multi-band pass filter [10] at narrow bands around the stimulation frequency and harmonics.	The optimal spatial filter results from maximizing an SNR estimate where the SSVEP signal power is approximated by $\mathbf{w}'\mathbf{C_X}\mathbf{w}$ and the noise power is approximated by $\mathbf{w}'\mathbf{C_X}\mathbf{w}+\mathbf{w}'\mathbf{C_Y}\mathbf{w}$. This approach requires training data (recorded during a calibration session).
minimum Energy Combination (mEC) [4]	$\mathbf{w} = \underset{\mathbf{w}}{\operatorname{argmin}}\left\{\|(\mathbf{X}-\mathbf{QX})\mathbf{w}\|^2\right\}$ $\mathbf{Q}$ is the projection matrix on the space spanned by sinusoidal components at the stimulation frequency and harmonics.	The optimal spatial filter results from minimizing an estimate of the noise. Given that $\mathbf{QX}$ is the projection on the space spanned by the SSVEP signals, $\mathbf{X}-\mathbf{QX}$ is orthogonal to such space and can be considered as noise.
Maximum contrast combination (MCC) [4]	$\mathbf{w} = \underset{\mathbf{w}}{\operatorname{argmin}}\{\frac{\|\mathbf{Xw}\|^2}{\|(\mathbf{X}-\mathbf{QX})\mathbf{w}\|^2}\}$	An SNR estimate is obtained here by taking the ratio between $\|\mathbf{Xw}\|^2$ and $\|(\mathbf{X}-\mathbf{QX})\mathbf{w}\|^2$.
Average MCC (aMCC)	$\mathbf{w} = \underset{\mathbf{w}}{\operatorname{argmin}}\{\frac{\mathbf{w}'\mathbf{C_X}\mathbf{w}}{\mathbf{w}'\mathbf{C_Z}\mathbf{w}}\}$ $\mathbf{C_Z}$ is the cov. matrix of signals $\mathbf{X}-\mathbf{QX}$	The SNR estimate is improved by using the covariance matrices $\mathbf{C_X}$ and $\mathbf{C_Z}$.

to estimate the optimal spatial filters. The most popular are summarized in Table I.

These methods can be categorized into two groups. In the first group of methods (NAT, BBC, PCA, and ICA in Table I) the SSVEP detection is optimized by taking the spatial filter which maximizes the estimate of the area under the receiving-operator-curve (AUC). Given that this is a detection problem, the AUC constitutes an appropriate performance indicator. The use of AUC in the framework of SSVEP detection is explained in detail in [11]. The AUC has values between 0 and 1, 1 is the highest value and indicates perfect detection performance.

The native (NAT) approach is the simplest method because it consists in selecting the signal of one single electrode to detect the SSVEP. In the best bipolar combination approach (BBC), a pair of electrodes is selected through exhaustive search. The PCA [5] and ICA [6] approaches use these well known techniques to obtain spatial filters that respectively lead to uncorrelated and statistically independent signals. Among these signals, one can select the ones that bring the highest AUC and use the corresponding spatial filters.

The second group of methods (CSP, mEC, MCC, and aMCC in Table I) utilize estimates of the SSVEP signal power, noise power, and/or signal-to-noise ratio (SNR) to obtain the optimal spatial filter. The estimate of the SSVEP power: $\mathbf{w}'\mathbf{C_X}\mathbf{w}$ is common to these methods. The covariance matrix $\mathbf{C_X}$ is estimated from a single EEG epoch $\mathbf{X}'\mathbf{X}$ in the maximum contrast combination (MCC) [4] method. The common spatial patterns (CSP) [7] and average MCC (aMCC) use averaging of several epochs recorded during a calibration phase to obtain a more robust estimate of $\mathbf{C_X}$.

The estimation of the noise power can be obtained using the epochs recorded during the absence of stimulation. This is the approach in the CSP method. The noise can also be directly estimated from the epochs where visual stimulation was presented. The projection operator $\mathbf{Q}$ in the space spanned by the SSVEP oscillations is first determined. Considerations about this operator are presented in detail in [11]. The epoch $\mathbf{QX}$ is in the SSVEP space and $\mathbf{X}-\mathbf{QX}$ is orthogonal to such space. The noise power can then be estimated by $\|(\mathbf{X}-\mathbf{QX})\mathbf{w}\|^2$. The minimum energy combination method (mEC) [4] directly minimizes the noise to obtain $\mathbf{w}$. An SNR estimate is maximized in the maximum contrast combination (MCC) [4] method. The aMCC method, improves the SNR estimation by considering the covariance matrix of epochs $\mathbf{X}-\mathbf{QX}$. We show in Section IV that this improvement leads to higher performance as measured by the AUC.

For reference, we also include in Table I the average combination method (AVG) which uses a simple additive combination of all the EEG recorded signals to detect the SSVEP. This actually corresponds to the CAR reference.

III. EXPERIMENTAL METHODS

Three male subjects (S1 to S3), aged ages 24, 29, and 31, participated in this experiment. They were requested to seat in front of a lamp positioned approximately one-meter away from their eyes. The lamp consisted of twelve LEDs, arranged in a 3x4 configuration, which shone through a white diffusion screen. The color temperature was of 4441.3K and the light luminance in the "on" state was of 460 Cd/m^2.

The EEG data of subjects was collected using an Active2 Biosemi system [12] at the 32 locations that are shown in Figure 5. As explained in Section IV, given the number of electrode sites and their distribution, we can apply the CAR to the recorded EEG. Subjects were presented with repetitive visual stimulation at 22 frequencies: 5Hz, 7Hz, 9Hz, 10Hz, 11Hz, 12Hz, 13Hz, 15Hz, 19Hz, 20Hz, 24Hz, 25Hz, 27Hz, 29Hz, 30Hz, 32Hz, 34Hz, 35Hz, 37Hz, 39Hz, 40Hz, and 45Hz. These were presented in four sessions. In the first three sessions, six stimulation frequencies (randomly selected) were used and in the fourth session four stimulation frequencies. Each stimulation frequency was presented once only. The sessions took place at around the same time of the day (early afternoon) to avoid circadian influences on the measurements.

The presentation of a given stimulation frequently was divided into thirty intervals which comprised a 4-second long stimulation period where the lamp flickered followed by a break period of random duration between 15 and 20 seconds. Such relatively long break period was chosen in order to ensure that consecutive stimulation periods are independent from each other. Indeed, as discussed in [11], the amplitude of the SSVEP decreases if the stimulation periods are too close from each other. Under these conditions, about ten minutes were required to present a stimulation frequency.

IV. RESULTS AND DISCUSSION

Unless otherwise specified, the EEG signals are all re-referenced to the common average reference. To illustrate the SSVEP manifestation in the EEG, we show in Figure 1, the power spectrum density at electrode Oz for a selection (multiples of 5) of stimulation frequencies from 5 to 45 Hz. In practice, the EEG spectrum limits to about 50 Hz. The scalp recorded EEG has relatively low frequency content because the relevant electrical activity occurs at the brain cortex level, i.e. several layers deeper from the measurement sites. The presence of harmonics is more prominent in the spectra corresponding to low stimulation frequencies. Considerations about the optimal number of harmonics for SSVEP detection are also discussed in Figure 3.

The AUCs for all the spatial filtering approaches and stimulation frequencies are depicted in Figures 2a, 2b, and 2c for subjects S1, S2, and S3 respectively. The AVG filter has the weakest performance overall. This is expected because the SSVEP has a well defined spatial specificity on the occipital and parietal sites. The range of stimulation frequencies where the SSVEP detection is the highest, is subject dependent. Yet, the 15 to 20 Hz band appears to be common for the three subjects in this study.

An important aspect is to consider the appropriate number of harmonics to detect the SSVEP. Intuitively we know that more harmonics need to be considered for low stimulation frequencies (below 30 Hz) and only the fundamental frequency for high stimulation frequencies (above 30 Hz). To confirm

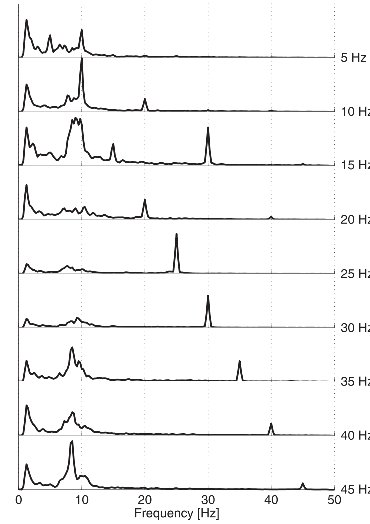


Fig. 1. Power spectrum density at electrode Oz (subject S1) for the multiple of 5 stimulation frequencies ranging from 5 to 45 Hz. The number on the right of each axis indicates the stimulation frequency. The units on the vertical axis are arbitrary and normalized to enhance visibility.

this, we have performed an exhaustive search to determine the optimal number of harmonics per method, subject, and stimulation frequency. We summarize our results in Figure 3 where we report, per stimulation frequency, the best number of harmonics estimated as the mode of the AUC distribution across subjects and detection method. The results confirm our intuition. Indeed, three harmonics appear to be needed for stimulation frequencies below 20 Hz.

It is possible to observe a drop in performance (Figure 2) for stimulation frequencies in the alpha band (8-13 Hz). This decrease can be explained by the fact that high (low) alpha activity is correlated with idleness (activity) at the cortical level [13]. However, when an RVS is presented, the primary visual cortex is supposed to be actively processing the stimulus which should lower the alpha level. It is well known that the alpha band limits is subject dependent, we have then determined the individual alpha peak frequencies for our subjects using the technique in [13]. By taking all the periods where no stimulation was presented we obtain the IAFs of S1, S2,and S3 which are respectively: 11.33 ± 0.37 Hz, 10.59 ± 0.22 Hz, and 9.16 ± 0.40 Hz. The rather small variances appear to indicate the stability of the IAFs.

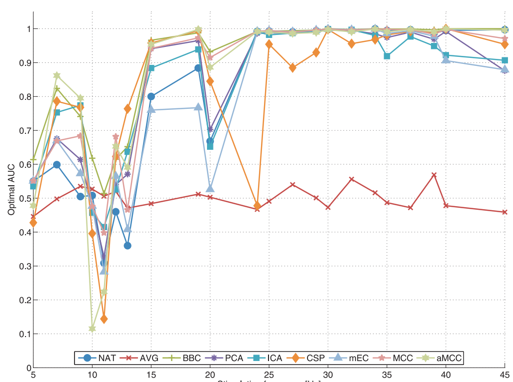
The difference in performance for each spatial filter depends on the stimulation frequency. Figure 2 suggests that the best methods overall are BBC, MCC, and aMCC. We have averaged the performance over all frequencies for each method and each subject. These results are reported in Table II. We have highlighted per each subject the top three methods. This indicates that the BBC, MCC, and aMCC methods lead to the best SSVEP detection performance.

In Figure 4, we depict the topographic representation of the spatial filters for subject S2 at the stimulation frequency of 15 Hz. The purpose of this representation is to visualize the sites

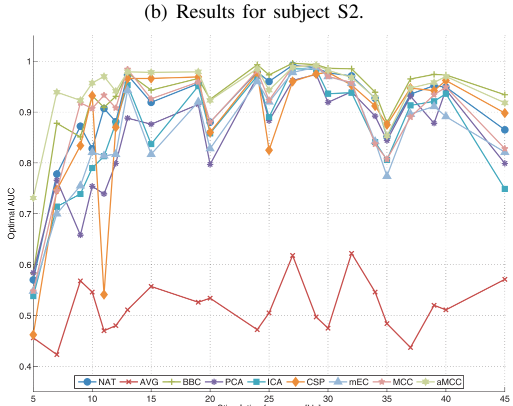
TABLE II
AVERAGE AUC OVER ALL STIMULATION FREQUENCIES FOR EACH METHOD AND SUBJECT

Subject	NAT	AVG	BBC	PCA	ICA	CSP	mEC	MCC	aMCC
S1	0.88 ± 0.12	0.53 ± 0.05	$\mathbf{0.90 \pm 0.09}$	0.82 ± 0.12	0.84 ± 0.11	0.81 ± 0.16	0.83 ± 0.16	$\mathbf{0.88 \pm 0.10}$	$\mathbf{0.91 \pm 0.08}$
S2	0.80 ± 0.25	0.50 ± 0.03	$\mathbf{0.88 \pm 0.17}$	0.82 ± 0.22	0.83 ± 0.20	0.81 ± 0.24	0.79 ± 0.24	$\mathbf{0.85 \pm 0.21}$	$\mathbf{0.84 \pm 0.26}$
S3	$\mathbf{0.90 \pm 0.09}$	0.51 ± 0.05	$\mathbf{0.93 \pm 0.09}$	0.85 ± 0.10	0.86 ± 0.11	0.81 ± 0.14	0.86 ± 0.11	0.90 ± 0.10	$\mathbf{0.94 \pm 0.06}$

(a) Results for subject S1.



(b) Results for subject S2.



(c) Results for subject S3.

Fig. 2. AUC for all spatial filtering approaches and stimulation frequencies.

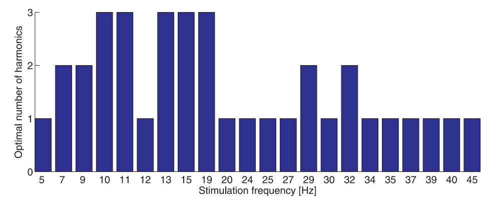


Fig. 3. Optimal number of harmonics for SSVEP detection versus stimulation frequency.

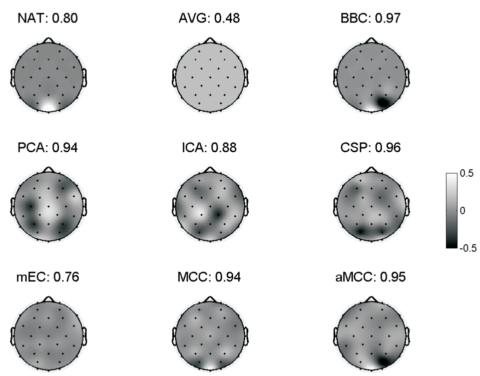


Fig. 4. Topographic representation of the spatial filters for each method for subject S2 at stimulation frequency of 15 Hz.

where the highest (lowest) coefficients (in absolute value) are localized. The concentration of large coefficients (in absolute value) on the occipital and parietal areas for the best methods indicate their physiological appropriateness.

The high performance associated with the BBC method suggests that two electrodes could be sufficient to detect the SSVEP. This has interesting practical implications because it can enable the design of a simple and convenient three-electrode (including the patient ground) measurement device which can be used in an SSVEP based BCI. This could be even more appealing if the same pair of electrodes would be appropriate for all users. To assess this possibility we have determined the BBC for all stimulation frequencies and subjects and determined how many times a given pair of electrodes corresponds to the BBC. We portray this result in Figure 5 where we use a connectivity diagram in which the thickness of the connecting line is directly related to the number of times that a given pair is selected as BBC (for clarity, we have only represented the pairs which are at least

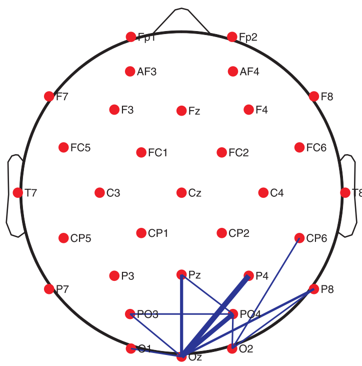


Fig. 5. Connectivity diagram illustrating the pairs which were more often selected as BBC.

two times selected as BBC). The pair Oz-P4 appears as the most frequently selected as BBC followed by Oz-Pz. The first shows a right hemisphere bias which may be related to the subjects dominant eye (right eye for all subjects). The pair Oz-Pz has interesting practical importance. Large scale experiments are necessary to confirm this.

V. CONCLUSIONS

In this paper, we have analyzed several spatial filter methods to detect the SSVEP from the EEG signals. We have proposed a taxonomy of methods according to the manner in which they optimize the spatial filter coefficients. We distinguish the methods that rely on the SSVEP detection performance and the ones which optimize estimates of the SSVEp signal power, noise power, and the SNR.

The detection performance depends on the stimulation frequency and the difference between methods is more prominent for stimulation frequencies below 10 Hz. There is a drop in performance for the stimulation frequencies in the vicinity of the alpha range (8-12 Hz). This can be explained by the alpha activity correlation with the idling state of the brain cortex.

The best methods for spatial filtering design are the aMCC, BBC, and MCC. The aMCC results from a minor modification of the MCC method which consists in using a more robust estimate of the covariance matrix.

The BBC method has a practical importance because it could enable the design of simple and convenient devices to detect the SSVEP from the EEG. In an attempt to universalize the location of the BBC, we have determined that the pair Oz-Pz could be an appropriate choice. More experiments need to be conducted to confirm this.

VI. ACKNOWLEDGMENTS

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REFERENCES

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

[2] Y. Wang, X. Gao, B. Hong, C. Jia, and S. Gao, "Brain-Computer Interfaces Based on Visual Evoked Potentials," *IEEE Engineering in Medicine and Biology Magazine*, vol. 27, no. 5, pp. 64–71, 2008.

[3] D. Zhu, J. Bieger, G. Garcia-Molina, and R. Aarts, "A survey of stimulation methods used in SSVEP-based BCIs," *Journal of Computational Intelligence and Neuroscience*, vol. Article ID 702357, 12 pages, 2010.

[4] 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*, vol. 54, no. 4, pp. 742–750, 2007.

[5] S. Pouryazdian and A. Erfanian, "Detection of Steady-State Visual Evoked Potentials for Brain-Computer Interfaces Using PCA and High-Order Statistics," in *World Congress on Medical Physics and Biomedical Engineering*, 2009.

[6] Y. Wang, Z. Zhang, X. Gao, and S. Gao, "Lead selection for SSVEP-based brain-computer interface," in *Proceedings of the 26th Annual International Conference of the IEEE EMBS 2004*, 2004, pp. 4507–4510.

[7] S. Parini, L. Maggi, A. Turconi, and G. Andreoni, "A Robust and Self-Paced BCI System Based on a Four Class SSVEP Paradigm: Algorithms and Protocols for a High-Transfer-Rate Direct Brain Communication," *Computational Intelligence and Neuroscience*, 2009.

[8] P. Nunez and R. Srinivasan, *Electric Fields of the Brain: The Neurophysics of EEG*. Oxford University Press, 2005.

[9] Y. Wang, R. Wang, X. Gao, B. Hong, and S. Gao, "A practical VEP-based brain-computer interface," *Neural Systems and Rehabilitation Engineering, IEEE Transactions on*, vol. 14, no. 2, pp. 234–240, 2006.

[10] M. Lang, C. Burrus, and I. Selesnick, "Constrained Least Square Design of FIR Filters Without Specified Transition Bands," *IEEE Trans. on Signal Processing*, vol. 44, pp. 1879–1892, 1995.

[11] G. Garcia-Molina and V. Mihajlovic, "Spatial filters to detect Steady State Visual Evoked Potentials elicited by high frequency stimulation: BCI application," *Journal of Biomedizinische Technik / Biomedical Engineering*, vol. 55, no. 3, pp. 173–182, 2010.

[12] Biosemi, "Biosemi system," http://www.biosemi.com.

[13] W. Klimesch, "EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis," *Brain research. Brain research reviews*, vol. 29, no. 2-3, pp. 169–195, 1999.