Analyzing Steady State Visual Evoked Potentials Using Blind Source Separation

Francois-Benoit Vialatte*†, Monique Maurice‡, Toshihisa Tanaka§, Yoko Yamaguchi ‡, Andrzej Cichocki*
* ESPCI ParisTech, Laboratoire SIGMA.
† Riken BSI, Lab. ABSP, Wako-Shi, Japan
E-mail: fvialatte,cia@brain.riken.jp Tel: +81-48-467-9668
‡ Riken BSI, Lab. DEI, Wako-Shi, Japan
E-mail: mvialatte,yokoy@brain.riken.jp Tel: +81-48-462-1111 Ext. 7424
§ Tokyo University of Agriculture and Technology, Department of Electrical and Electronic Engineering,
E-mail: tanakat@cc.tuat.ac.jp Tel: +81-42-388-7439

***Abstract*—The present study seeks to investigate the limits of scalp EEG (electroencephalogram) SSVEP (Steady State Visual Evoked Potentials) phenomena (to which maximal and minimal frequencies SSVEP can be recorded at the scalp level). SSVEP are periodic evoked signals buried in the non-stationary waves of EEG recordings. EEG signals are furthermore noisy and contain artifacts which may interfere with brain signals. Our primary objective is therefore to enhance and/or extract SSVEP signals, and to reject the possibility of artifacts. Because EEG is recorded by several electrodes distributed over the scalp, and SSVEP have wide spatial extents, blind source separation can be used to enhance SSVEP responses. We explore the potential of blind source separation for SSVEP extraction and analysis, using the IWASOBI algorithm.**

I. Introduction

SSVEP (Steady State Visual Evoked Potentials) are evoked responses induced by flickering visual stimuli. SSVEP are periodic, with a stationary distinct spectrum showing characteristic SSVEP peaks, stable over time (see [1] for review).The usually 'accepted' limits of SSVEP are in the 3-60 Hz range. What happens below and above these frequencies is not well-documented. Recent studies reported SSVEP activities outside of this range (1-100 Hz EEG in [2], 0-20 Hz MEG in [3], 0.5-5 Hz EEG in [4]). The present study seeks to investigate the limits of scalp EEG SSVEP phenomena (to which maximal and minimal frequencies SSVEP can be recorded at the scalp level). The first step to acheive this purpose is to evaluate if observed SSVEP peaks can be attributed to muscular artifacts, especially in the theta and gamma ranges, where artifacts could create fake peaks (for instance, eye blinks induced by the stimulation could be confused with regular SSVEP peaks).

In neuroscience, contrary to neuroengineering studies, SSVEP studies used until now mostly classical methods to identify the evoked responses: superposition, averaging, frequency analysis, or correlation analysis (e.g. [5]). However, EEG signals are noisy and contain artifacts which may interfere with brain signals (instrumental noise and environmental noise, movement and other physiological noise). Artifacts in the EEG can be defined as any potential difference due to an extra-cerebral source [6]. the frequency range of muscle artifacts and the EEG overlap to a high degree [7]. This means that muscle artifacts can appear as electrical patterns which are very hard to differentiate from the brain EEG signals, and are consequently especially problematic. In addition to these extracerebral signals, brain activity that is not related to SSVEP could also be considered as noise. Consequently, more recent approaches aim to enhance the SSVEP signal using mathematical models (see [1] for a recent review).

Blind Source Separation (BSS) is a method which can be used to recover underlying signals from linear mixtures of those signals. BSS is especially useful to reject EEG artifacts [8], exploiting statistical independent criteria to separate EEG sources, which allows to remove artifacts and clean EEG [9]–[11]. Therefore, it has been often used for analysis of EEG. It seems therefore natural to apply this method to control if SSVEP effects observed in the lower and higher frequency ranges are due to muscular artifacts, or brain potentials. To the best of our knowledge, such a study was never performed.

The SSVEP is a periodic signal buried in the non-stationary waves of EEG recordings; our objective is to enhance and/or extract that signal. In order to enhance SSVEP, several signal processing methods have been suggested. Because EEG is recorded by several electrodes distributed over the scalp, and SSVEP have wide spatial extents, blind source separation can be used to enhance SSVEP responses [12]–[14]. We explore the potential of blind source separation for SSVEP extraction and analysis, using the IWASOBI algorithm contained in the ICALAB package.

II. Methods

Computations were done with Matlab (The MathWorks, Inc.), BSS cleaning was performed using ICALAB ver. 3 with automatic sorting of independent components [15].

A. EEG Data

EEG data was recorded in a shielded room, on 8 subjects (all females, right handed). Recording was performed using Biosemi caps with 128 electrodes, + 2 neck EMG sensors, and 1 EOG channel. Signal was sampled at 1024 Hz, bandpass filtered in the [0.5-220] Hz range.

Proceedings of the Second APSIPA Annual Summit and Conference, pages 578–582,
Biopolis, Singapore, 14-17 December 2010.

SSVEP was evoked using 21 frequencies from 1 to 100 Hz, displayed in a pseudo-randomized order; and the same sequence of frequencies is presented to all subjects. The 21 frequencies were distributed in order to regularly match the harmonics of 10 Hz: [1.0; 1.25; 1.88; 2.5; 3.3; 4.17; 5.0; 6.6; 8.3; 10.0; 13.3; 16.6; 20.0; 26.6; 33.3; 40.0; 53.3; 66.6; 80.0; 90.0; 100] Hz. Each trial consisted of 20 sec. of rest condition followed by 15 sec. of stimulation. Three trials were recorded for each frequency (total = 63 trials per subject). Stimulation consisted of flickering white screens, displayed using Avotec optic fiber goggles (Silent Vision googles, visual angle 18x24^o). During stimulation, subjects saw a flickering white/black light generated with a Silent Vision shutter to control high frequency refreshment rates. During fixation subject saw a gray background, isoluminant with the stimuli.

B. Blind Source Separation

Blind Source Separation (BSS) consists in recovering a set of unknown sources from their observed mixture $\mathbf{x}$. The linear and instantaneous models of BSS can be formulated as:

$$\mathbf{x} = \mathbf{A}\mathbf{s} \tag{1}$$

where $\mathbf{s}$ represents a data matrix having as rows the observed signals, and $\mathbf{A}$ is the mixing matrix. According to the currently prevailing view of EEG signal processing, a signal can be modeled as a linear mixture of a finite number of brain sources, with additive noise (see *e.g.* [9]–[11]). Therefore, blind source separation techniques can be used advantageously for decomposing raw EEG data to brain signal subspace and noise subspace. If sources are supposed to be independent, then BSS can be called ICA.

The Second-Order Blind Identification (SOBI) algorithm is a well-known blind source separation (BSS) method for source signals with temporal structures and distinct spectra (AR processes). It already proved to be useful in many biomedical applications. A weight adjusted version of SOBI was suggested in [16]. SOBI jointly (approximately) diagonalizes time-delayed covariance matrices for many time delays. However, the SOBI algorithm does not specify how many and which time delays to choose. An efficient weight adjusted variant of SOBI called IWASOBI [17], [18] was recently developed to solve this problem. The original weight adjusted SOBI used a standard AJD (Approximative Joint Diagonalization) algorithm.IWASOBI uses instead an AJD based on family of WEDGE[1] algorithms [17].

SOBI minimizes the following criterion:

$$C(\mathbf{A}, \lambda) = [\hat{\mathbf{y}} - I \otimes G(\mathbf{A})\lambda]\mathbf{W}[\hat{\mathbf{y}} - I \otimes G(\mathbf{A})\lambda] \tag{2}$$

Where $\hat{\mathbf{y}}$ represents the sources to be estimated, $\mathbf{A}$ is the mixing matrix,, $\otimes$ the kronecker product, G denotes a normalized Kathri-Rao product, λ is the diagonal of the correlation matrix of $\mathbf{x}$, and $\mathbf{W}$ is a weight matrix. The purpose of SOBI is therefore to extract a set of sources $\hat{\mathbf{y}}$, and a mixing matrix $\mathbf{W}$, from the observed signals $\mathbf{x}$. The improved WASOBI estimates a re-ordered $\mathbf{W}$ (noted $\tilde{\mathbf{W}}$) after reordering of the sources $\hat{\mathbf{y}}$:

$$C(\mathbf{A}, \lambda) = [\tilde{\mathbf{y}} - \tilde{G_0}(\mathbf{A})\lambda]\tilde{\mathbf{W}}[\tilde{\mathbf{y}} - \tilde{G_0}(A)\lambda] \tag{3}$$

Thanks to this re-ordering, the number of jointly diagonalized covariance matrices can be relatively low using IWASOBI in comparison to the standard SOBI; while performance can be considerably higher. This algorithm allows reliable separation of 100+ sources with temporal structure (autoregressive sources) in order of seconds. Where $\tilde{\mathbf{y}}$ are the estimated sources ($\tilde{\mathbf{y}} \approx \mathbf{s}$).

In our experiments we used the IWASOBI algorithm implemented in ICALAB ver.3 [15].

C. Cleaning Rules

A trained scientist inspected all EEG recordings. Each trial was decomposed using IWASOBI. Sources were ordered using a kurtosis measure, and up to one third of the sources were rejected for each trial (eye movements, electromyographic corruption, electrocardiographic artifact, etc), using four criteria:

1) Abnormal scalp distribution of the reconstructed channels (only a few electrodes contribute to the source, with an isolated topography).
2) Abnormal wave shape (drifts, eye blinks, sharp waves, etc.).
3) Source of abnormally high amplitude ($\geq$ 100 μV).
4) Source providing from electromyographic or electrooculographic sensors.

We have focused our attention mainly on the smallest and largest values of kurtosis (i.e. a measure of sparsity and distance to Gaussianity), which are more likely to be representative of artifacts. The purpose, as explained above, was to control that the studied effects in very high (above 40 Hz) and very low (below 3 Hz) frequencies were not due to artifacts, but to brain signals. After this step, the remaining sources were back-projected onto the scalp, yielding an artifact clean data (see *e.g.* figures 1 and 2).

D. Fourier Power Analysis

The Fourier power $\mathbf{\Phi}$ was computed using FFT over the whole signals (resolution = 0.1 Hz). The signal-to-noise ratio of SSVEP $\mathbf{SNR}(f_p)$ was afterwards computed using the ratio of Fourier power at a given frequency f_p to its n-adjacent frequencies power:

$$\mathbf{SNR}(f_p) = \frac{n.\mathbf{\Phi}(f_p)}{\sum_{k=s}^{s.n/2} \mathbf{\Phi}(f_p + k) - \sum_{k=s}^{s.n/2} \mathbf{\Phi}(f_p - k)} \tag{4}$$

with n pair. This SNR measure acts as a high-pass filter on the Fourier domain (letting only sharp Fourier peaks pass), and have been used successfully to enhance SSVEP peaks [19]. We used $n = 6$, so that the frequencies $f_p \pm 0.6$ Hz were taken into account. Fourier power and SNR were computed for each trials, and averaged afterwards. Computations were done with Matlab (The MathWorks, Inc.). Results presented here come from the channel Oz.

[1]Weighted Exhaustive Diagonalization using Gauss itEration

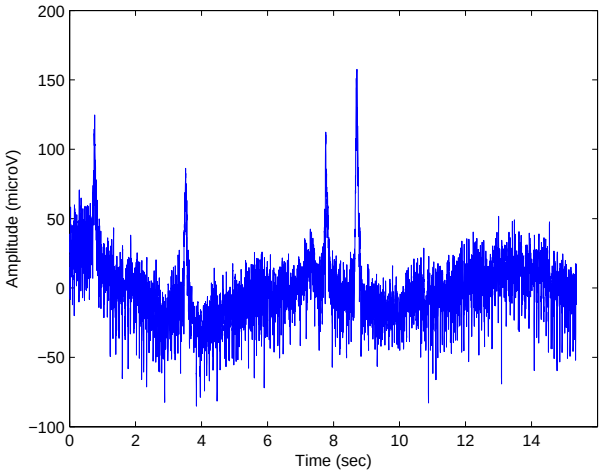

Fig. 1. Typical example, after BSS cleaning (here, frontal response to a 20 Hz stimulation, with visible eye blinks).

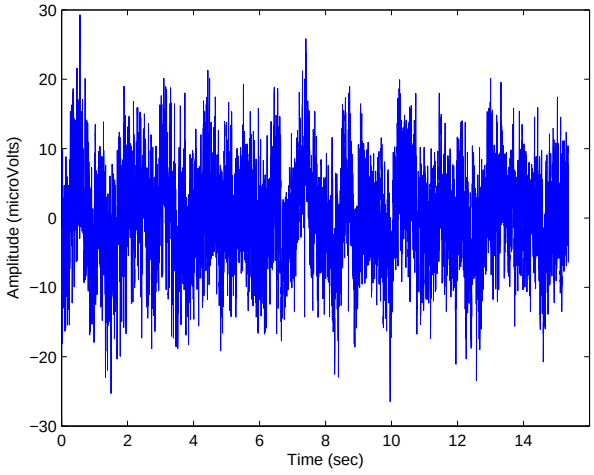

Fig. 2. Typical example, before BSS cleaning (same signal as 1, after cleaning procedure).

III. Results

We confirmed the presence of SSVEP activity in low frequency ranges (down to 1 Hz, see Fig.3), that we already reported before [4]. We also observed SSVEP in high frequencies (Fig.4): stimulation at 40 Hz induced an SSVEP, with 80 Hz harmonics. Stimulation up to 66.7 Hz induced SSVEP. Stimulations above 80 Hz did not induce visible SSVEP.

IV. Conclusions

We have already demonstrated the existence of low frequency SSVEP (0.5-5 Hz) in a previous publication [4]. Our present result confirms this previous observation. We did observe SSVEP for all the low frequency range stimulations.

SSVEP above 80 Hz were reported before [2]. In our experiment, stimulations up to 66.7 Hz induced SSVEP, but not above. This discrepancy might be due to several reasons:

- The stimuli might be too weak: Avotec goggles might have insufficient brightness, or insufficient contrast when the shutter operates with such high frequencies. Some trials (but not all) seem to display 100 Hz SSVEP responses, which would support this hypothesis.
- Scalp EEG may not be appropriate to record such high frequencies. The different layers separating the brain from the electrodes act as low-pass filters, and therefore reduce the quality of the signal for high frequencies.
- The SNR method might be inappropriate to enhance this activity. High frequencies have wider frequency uncertainty, hence an adaptive SNR (n varying depending on the frequency) might be more appropriate. Similarly, other BSS methods could be used. For instance, instead of reoving artifacts, one coud rank the sources according to their likelihood to contain SSVEP.

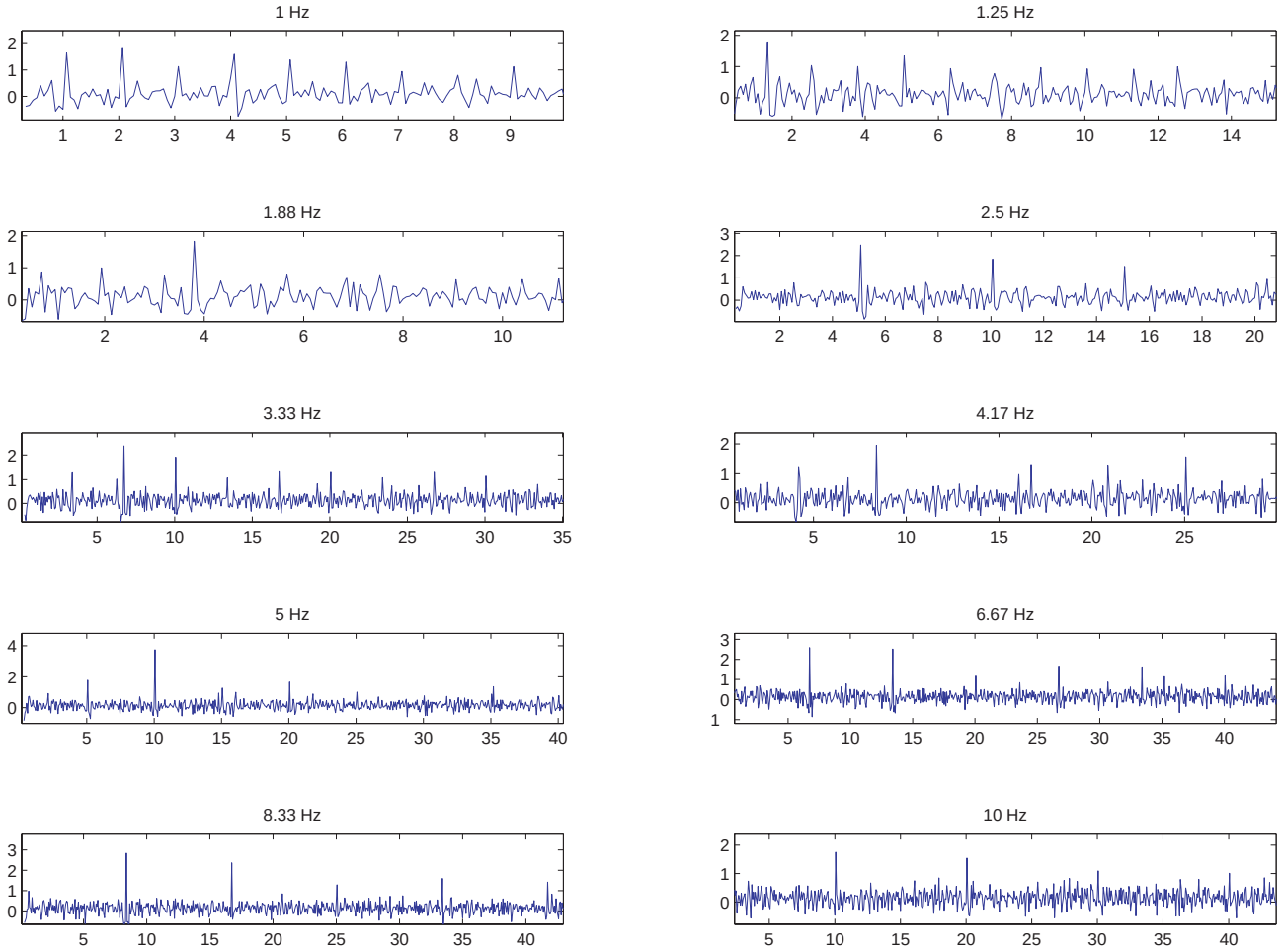

Fig. 3. SSVEP SNR with respect to frequency, measured for low frequency stimulations.

The third question can be addressed by developing new mathematical representations for SSVEP signals: these signals have narrow peaks, and stereotyped responses, which could possibly de detected using an appropriate model. For instance, by generalizing the Victor-Mast test [20] to take into account SSVEP harmonics, one could obtain a reliable detection of SSVEP sources to derive an automatic BSS for SSVEP. Otherwise, one could train classifiers that try to distinguish presence/absence of SSVEP at particular frequency. The higher the accuracy of the classifiers for particular frequency, the stronger the detectability of SSVEP. Of course, that measure would then depend on the type of classifier used, and on its parameters. This will be the object of a future study.

We have confirmed the presence of SSVEP from 1 to 66.7 Hz, and controlled that these effects are not likely to be attributed to artifacts.

ACKNOWLEDGMENT

Monique Maurice was supported by the JSPS fellowship P08811.

REFERENCES

[1] Vialatte, F., Maurice, M., Dauwels, J., Cichocki, A.: Steady-state visually evoked potentials: Focus on essential paradigms and future perspectives. Progress in Neurobiology **90** (2010) 418–438

[2] Herrmann, C.: Human eeg responses to 1-100 hz flicker: resonance phenomena in visual cortex and their potential correlation to cognitive phenomena. Exp Brain Res **137**(3-4) (2001) 346–53

[3] Fawcett, I., Barnes, G., Hillebrand, A., Singh, K.: The temporal frequency tuning of human visual cortex investigated using synthetic aperture magnetometry. Neuroimage **21**(4) (2004) 1542–53

[4] Vialatte, F., Maurice, M., Dauwels, J., Cichocki, A.: Steady state visual evoked potentials in the delta range (0.5-5 hz). In: 15th International Conference on Neural Information Processing, ICONIP, Auckland, New Zealand, November 25-28 2008 ICONIP 2008, LNCS, Part I, 5506:399-406. (2009)

[5] Spekreijse, H., Estevez, O., Reitz, D.: Visual evoked potential and the physiological analysis of visual process in man. In Desmedt, J., ed.: Visual Evoked Potentials in Man: New Developments. Clarendon, Oxford (1977) 16–85

[6] Anderer, P., Roberts, S., Schlogl, A., Gruber, G., Klosch, G., Herrmann, W., Rappelsberger, P., Filz, O., Barbanoj, M., Dorffner, G., Saletu, B.: Artifact processing in computerized analysis of sleep eeg - a review. Neuropsychobiology **40**(3) (1999) 150–157

[7] Van de Velde, M.: Signal Validation in Electroencephalography Research. PhD thesis, echnische Universiteit Eindhoven, Netherlands. (2000)

[8] Ille, N., Berg, P., Scherg, M.: Artifact correction of the ongoing eeg using

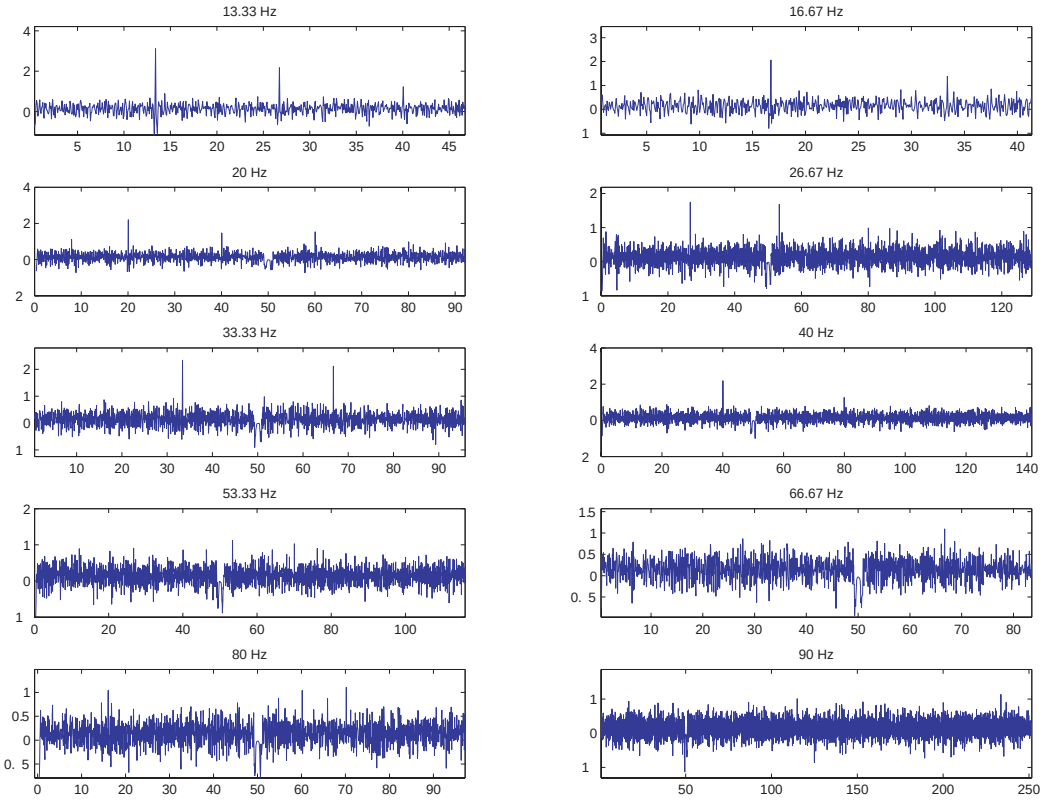

Fig. 4. SSVEP SNR with respect to frequency, measured for high frequency stimulations (the gap around 50 Hz corresponds to the notch filter).

spatial filters based on artifact and brain signal topographies. Journal of Clinical Neurophysiology **19**(2) (2002) 113–124

[9] Jung, T., Makeig, S., Humphries, C., Lee, T.W., McKeown, M., Iragui, V., Sejnowski, T.: Removing electroencephalographic artifacts by blind source separation. Psychophysiology **37** (2000) 163–178

[10] Cichocki, A.: Blind signal processing methods for analyzing multichannel brain signals. International Journal of Bioelectromagnetism **6**(1) (2004)

[11] Cichocki, A., Shishkin, S., Musha, T., Leonowicz, Z., Asada, T., Kurachi, T.: Eeg filtering based on blind source separation (bss) for early detection of alzheimer"s disease. Clinical Neurophysiology **116**(3) (2006) 729–737

[12] Li, X.O., Zhang, X.W., Feng, H.Q.: Real time extraction of visual evoked potentials. In: Proc. Conf. Neural Networks and Signal Processing, 2:1342-1345. (2003)

[13] Wang, Y., Wang, R., Gao, X., Hong, B., Gao, S.: A practical vep-based brain-computer interface. IEEE Trans. Neural Syst. Rehabil. Eng. **14**(2) (2006) 234–239

[14] Wang, Y., Zhang, Z., Gao, X., Gao, S.: Lead selection for ssvep-based brain-computer interface. In: Proc. IEEE EMBS, 6:4507-4510. (2004)

[15] Cichocki, A., Amari, S., Siwek, K., T, T., A-H., P.: Icalab version 3 toolbox

[16] Yeredor, A.: Blind separation of gaussian sources via second-order statistics with asymptotically optimal weighting. IEEE Signal Processing Letters **7** (2000) 197–200

[17] Tichavský, P., Yeredor, A., Nielsen, J.: A fast approximate joint diagonalization algorithm using a criterion with a block diagonal weight matrix. In: Proc. ICASSP 2008, Las Vegas, U.S.A. (2008)

[18] Tichavský, P., Doron, E., Yeredor, A., Nielsen, J.: Computationally affordable implementation an asymptotically optimal bss algorithm for ar sources. In: EUSIPCO 2006, Florence, Italy. (2006)

[19] Wang, Y., Wang, R., Gao, X., Hong, B., Gao, S.: Vep-based brain-computer interface. IEEE Trans Neural Syst Rehabil Eng **14**(2) (2006) 234–239

[20] Mast, J., Victor, J.: A new statistic for steady-state evoked potentials. Electroencephalography and Clinical Neurophysiology **78** (1991) 378–388