SIMPLE AND EFFICIENT METHODS FOR STEADY STATE VISUAL EVOKED POTENTIAL DETECTION IN BCI EMBEDDED SYSTEM

Niccolò Mora, Valentina Bianchi, Ilaria De Munari and Paolo Ciampolini

Information Engineering Department, University of Parma
Parco Area delle Scienze 181/A, 43124 Parma, Italy

ABSTRACT

Brain Computer Interfaces (BCI) can provide severely impaired users with alternative communication paths, by means of interpretation of the user's brain activity. Among BCI operating paradigms, SSVEP is largely exploited for its potentially high throughput and reliability. In this paper, two novel SSVEP processing algorithms are presented, focused on calibration-free operation and computational efficiency, targeted for development of BCI embedded modules. A comparison with other popular SSVEP signal processing algorithm (MEC, AMCC, CCA) is also made; results demonstrate the feasibility and effectiveness of the proposed solutions.

Index Terms— Brain Computer Interface (BCI), SSVEP, MEC, AMCC, CCA.

1. INTRODUCTION

Brain Computer Interfaces (BCI) [1] are alternative, augmentative communication means that aim at providing the user (for instance lacking voluntary muscle control) with an interaction path, based on the interpretation of her/his brain activity. Currently, ElectroEncephaloGraphy (EEG) is the most widespread, non-invasive technique for extracting information on brain activity, due to its good overall tradeoff between temporal resolution and spatial resolution, as well as to its relatively lower costs.

Focusing on EEG-based BCI, several paradigms are commonly exploited for regulating their operation. Among them: Slow Cortical Potentials (SCP) [2], Event Related De/Synchronization (ERD/S) [3], P300 [4]-[5], Steady State Visual Evoked Potentials (SSVEP) [6]-[9]. The latter paradigm, in particular, exploits the natural brain response to a continuous, repetitive visual stimulus, such as a blinking LED: in the 4-50 Hz frequency range, the flashing frequency reflects on the onset of an isofrequency component in the brain power spectrum. By simultaneously presenting multiple visual stimuli, each one operating at a different frequency, the user's brain response can be analyzed to infer to which stimulus he was aiming.

The SSVEP paradigm is largely exploited in applications where Information Transfer Rate (ITR, defined in [1]) maximization is of primary concern, e.g. in spellers. Nonetheless, SSVEP responses are regarded as reliable features [6] for BCIs, given their inherent higher SNR (*Signal to Noise Ratio*). Finally, even if SSVEP-based BCIs usually require some residual ocular motor ability, recent studies on independent, covert attention based BCI are being carried out [8].

In [9] we presented the development of a platform (encompassing both hardware and software design aspects) conceived for prototyping of BCI embedded systems, specifically targeted to - even if not limited to - Ambient Assisted Living (AAL) control purposes. The platform is composed of three main units: *i)* an Analog Front End (AFE) for the acquisition of the EEG signal, *ii)* a digital signal processing unit, implementing feature extraction and classification and, *iii)*, an output/feedback unit for display and implementation of active controls. We started from developing and testing a novel hardware AFE unit, aiming at a compact and inexpensive circuit. To this regard, also the electrode technology choice (standard, passive *Ag/AgCl* wet contacts) and the electrode count (up to 6 EEG channels) were optimized, looking for costs reduction and user's comfort. Signal processing and feedback units are currently implemented on a PC architecture, allowing for more flexible testing and for better tuning performance. Nevertheless, the algorithms are specifically targeted for implementation on compact, portable devices, paying attention to devising computationally-efficient methods.

In particular, our approach aims at developing tools and methods for low-cost, standalone embedded BCI modules, making high-performance acquisition hardware or large computing powers unnecessary.

Following these premises, we present here two SSVEP signal processing algorithms we have designed and tested: both are fully calibration-free and suitable for low-resource computing platform. The first algorithm attempts to maximize accuracy, while the second one follows a complementary approach, aimed at improving the ITR. To validate the proposed approaches, comparison of such methods with other common signal-processing techniques frequently encountered in BCI applications is carried out.

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The paper is organized as follows: in section 2 some popular SSVEP signal processing methods are reviewed, while section 3 introduces the novel algorithms proposed. In section 4, accuracy, ITR and computational efforts of the aforementioned methods are compared. Finally, conclusions are drawn in section 5.

2. SSVEP SIGNAL PROCESSING METHODS

Many signal processing methods are commonly exploited in SSVEP-based BCI. A full review goes beyond the scope of this paper; the interested reader can refer, for example, to [10]. Here we shall limit ourselves to discuss three popular methods: *Minimum Energy Combination* (MEC) [7], *Average Maximum Contrast Combination* (AMCC) [11], *Canonical Correlation Analysis* (CCA) [12]. In general, the objective is to find a spatial filter **w** (i.e., a linear combination of the input channels) or a set of spatial filters, with the aim of increasing the accuracy of the classification process.

Minimum Energy Combination attempts to find an optimal spatial filter from minimizing an estimate of the noise. In particular, the voltage time series of a single electrode $y_i(t)$, can be modeled as:

$$y_i(t)=\sum_{k=1}^{Nh}\left(a_{i,k}\sin 2\pi kft+b_{i,k}\cos 2\pi kft\right)+E_i(t), \quad (1)$$

where the first term is the model of a SSVEP response corresponding to a stimulus frequency f (considering up to N_h harmonics), and $E_i(t)$ is a noise and nuisance signal. Given an EEG epoch of N_t samples, the input signals from the N_y electrodes can be represented as a matrix $\boldsymbol{Y}$ of size $N_t \times N_y$, whose columns are the potential readings from each electrode site. In the same way we can represent the SSVEP term in eq. (1) as a multiplication between a SSVEP information matrix $\boldsymbol{X}$ having size $N_t \times 2N_h$ and containing N_h (*sin*, *cos)* column pairs, and a weight matrix $\boldsymbol{G}$ of size $2N_h \times N_y$, containing all the $a_{i,k}$, $b_{i,k}$ coefficients. Eq. (1) then becomes:

$$Y = XG + E \quad (2)$$

To extract discriminant information, signals from the electrodes are combined with appropriate weight vectors **w** $[w_1, \ldots ,w_{Ny}]^T$. New channel vectors **s** of length N_t are then obtained as:

$$s=\sum_{i=1}^{N_y} w_i y_i = Yw, \quad (3)$$

which generalizes to N_s channels as follows:

$$S = YW, \quad (4)$$

where $\boldsymbol{S}=[\mathbf{s}_1, \ldots ,\mathbf{s}_{Ns}]$ represents the set of channels and $\boldsymbol{W}=[\mathbf{w}_1, \ldots , \mathbf{w}_{Ns}]$ is the corresponding weight matrix. Then, MEC proceeds as follows: at first, an orthogonal projection is used to remove any potential SSVEP activity from the recorded signal:

$$\widetilde{Y} = Y - X\left(X^T X\right)^{-1} X^T Y \quad (5)$$

$\tilde{Y}$ then approximately contains only noise, artifacts and background brain activity. An optimal set of N_s weight vectors $\hat{\mathbf{w}}$ must be then chosen such that the energy of the signal $\tilde{\boldsymbol{Y}}$ is minimized:

$$\min_{\hat{w}} \left\|\widetilde{Y}\hat{w}\right\|^2 = \min_{\hat{w}} \hat{w}^T \widetilde{Y}^T \widetilde{Y}\hat{w} \quad (6)$$

As shown in [7], the optimal solution is the eigenvector $\boldsymbol{v_1}$ that corresponds to the smallest eigenvalue λ_1 of the matrix $[\tilde{\boldsymbol{Y}}^T\tilde{\boldsymbol{Y}}]$. The weight matrix is then composed using the eigenvectors, corresponding to the N_s smallest eigenvalues, sorted in ascending order:

$$W = \left[\frac{v_1}{\sqrt{\lambda_1}} \cdots \frac{v_{N_s}}{\sqrt{\lambda_{N_s}}}\right]. \quad (7)$$

N_s is selected by finding the smallest number k which makes the sum of the k smallest eigenvalues greater than 10% of the sum of all the eigenvalues. This can be interpreted as selecting the number of channels in such a way as to discard as close to 90% of the nuisance signal energy as possible.

Finally, features are extracted according to the following equation:

$$\hat{P} = \frac{1}{N_s N_h}\sum_{l=1}^{N_s}\sum_{k=1}^{N_h}\left\|X_k^T s_l\right\|^2 \quad (8)$$

The process described so far is repeated for each stimulus frequency f, and a classifier picks the attended stimulus frequency.

Average Maximum Contrast Combination is similar to MEC up until eq. (5). It then attempts to maximize the SNR by optimizing the following equation:

$$\min_{\hat{w}} \frac{\hat{w}^T C_Y \hat{w}}{\hat{w}^T C_{\widetilde{Y}} \hat{w}}, \quad (9)$$

where $\boldsymbol{C_Y}$ and $\boldsymbol{C_{\tilde{Y}}}$ are the covariance matrices of signals $\boldsymbol{Y}$ and $\tilde{\boldsymbol{Y}}$, respectively. Again, minimization of the generalized Rayleigh quotient in (9) yields optimal weight vectors which can be used to construct the weight matrix $\boldsymbol{W}$ accordingly.

Canonical Correlation Analysis is generally used for finding the correlations between two sets of multi-dimensional variables. It seeks a pair of linear combinations, called canonical variables, for two sets, such that the correlation between the two canonical variables is maximized. Then it finds a second pair, uncorrelated with the first one, that has the second highest correlation. The process continues until the number of pairs of canonical variables equals the number of variables in the smallest set.

CCA can be applied to SSVEP detection by attempting to maximize the correlation between the input signals $\boldsymbol{Y}$ and the SSVEP information matrix $\boldsymbol{X}$, for each stimulus frequency. As features, the maximum CCA scores are used for classification.

3. PROPOSED SSVEP PROCESSING ALGORITHMS

In this section, two novel algorithms are presented, both featuring low computational demand and thus suitable for low-cost embedded implementation. **Algorithm 1**, introduced in [9], attempts to maximize accuracy: it is based on *Power Spectral Density* (PSD) analysis and aims at improving classification accuracy by *ad hoc* optimization of the feature extraction. At first, acquired data is digitally low-pass filtered (f_{cut}=40 Hz) for out-of-band noise reduction. Optionally, further pre-processing steps may include spatial filtering, such as a re-referencing of electrodes according to *Common Average Reference* (CAR) filter topology, or the creation of bipolar leads. PSD are estimated by Welch's method: the window length can be tuned for different speed vs. accuracy tradeoffs, as shown in Table 1. The channel powers are equalized over a given pre-determined band of interest. Normalization is shown to slightly improve the classification performance, especially in case of a strong inter-channel imbalance, due to, for example, different electrode impedance; it improves the classification robustness by somehow self-adapting to such variable scenarios.

The algorithm then exploits the *a priori* knowledge of the actual set of stimulation frequencies, checking the conditions only on such a set: the channel powers are summed for each target frequency. Candidate targets are selected whenever a given fraction (e.g., at least 50%) of the channels exhibit a local maximum in the PSD at the target frequency. If at least one candidate target exists, the sum of such powers are compared and the most probable frequency is picked, if larger enough (i.e., exceeding a given probability threshold). If no candidate targets were found in the previous step, comparison is made between the sum of powers at each frequency and classification is performed in the same way, accounting for a higher threshold.

Since the algorithm involves only relative comparisons, it virtually requires no calibration at all. Fine tuning of the algorithm is still possible by adjusting the classifier's parameters, such as the fraction of channels required to pick a candidate frequency or the relative threshold used by the classifier. Moreover, signal processing just involves operations well suitable for implementation on embedded devices, allowing to take full advantage of specialized digital signal processing hardware.

Algorithm 2 still retains calibration-free operation and computational efficiency, but privileges ITR maximization rather than accuracy, somehow complementing the previous approach.

Similarly to MEC and AMCC methods, a SSVEP information matrix $\boldsymbol{X}$ of size $N_t \times 2N_h$ is built for each stimulus frequency:

$$X = \begin{bmatrix} \sin 2\pi f t_1 & \cos 2\pi f t_1 & \cdots & \sin 2\pi N_h f t_1 & \cos 2\pi N_h f t_1 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \sin 2\pi f t_{Nt} & \cos 2\pi f t_{Nt} & \cdots & \sin 2\pi N_h f t_{Nt} & \cos 2\pi N_h f t_{Nt} \end{bmatrix} \quad (10)$$

Suitable filtering is applied to remove low frequency and out-of-band contributions. Then, input channels are normalized in order to have the same variance. Projection on the space spanned by the sinusoidal components of $\boldsymbol{X}$ is performed to remove any potential SSVEP activity from the recorded signal, as in eq. (5). The difference in variance before and after each projection, summed along all channels, are taken as features. Such simplified feature extraction procedure involves less steps than previously mentioned methods, and thus better suits implementation on small embedded devices. As far as classification is concerned, the matrix $\boldsymbol{X}$ which induces the larger decrease in the overall variance is assumed as the stimulus frequency. As in the previous algorithm, relative comparisons are exploited, thus avoiding calibration needs.

4. COMPARISON OF SSVEP ALGORITHMS

In order to assess the performance of the proposed algorithms, and to compare them with other signal processing methods, a 4 class SSVEP experiment was set up. Four healthy volunteers (age 22-27, with normal or corrected to normal vision) were asked to stare at one of the four simultaneous flickering LED while resting on an armchair at approximately 1 m from the visual stimulus. Each trial lasted for 6 seconds, and each LED presented a different stimulation frequency (16, 18, 20, 22 Hz); EEG was acquired at 250 SPS (*Samples Per Seconds*) with our custom hardware unit [9] from 6 scalp locations (namely O1, O2, P3, P4, P5, P6), using standard 10 mm Ag/AgCl disk electrodes with conductive paste. All algorithms were tested on the same EEG samples.

First, performances of Algorithm 1 are considered, shown in Table 1 *(a)*: to account for reliable PSD estimation, relatively longer epochs were needed, this of course reflecting on poor ITR; nevertheless, accuracy is fairly better than reference methods, even at comparable ITR. Such figures are particularly relevant when looking at environmental control application: in such a situation, indeed, we aim at minimizing the user effort for a given operation, which is supposed to be performed not too frequently. Hence, we focused on accuracy instead of speed.

Table 1 *(b)* shows, instead, the comparison between MEC, AMCC, CCA and our Algorithm 2. In this case, more emphasis is placed on ITR, and a shorter EEG window length is adopted for all methods. With the adopted 1.5 s

Table 1 Comparison of different SSVEP algorithms in terms of accuracy and Information Transfer Rate [bit/min] (lower row, in brackets). In *(a)*, the full 6 s EEG epoch is used for Algorithm 1; in *(b)*, a 1.5 s EEG window is used for all mentioned algorithms.

(a)

Subj.	3 s	4 s	5 s	6 s
1	90.0% (27.45)	83.3% (16.27)	86.7% (14.66)	90.0% (13.73)
2	91.7% (29.08)	91.7% (21.81)	100% (24.00)	100% (20.00)
3	87.5% (25.17)	95.0% (24.52)	92.5% (17.96)	97.5% (17.92)
4	94.1% (31.68)	94.1% (23.76)	94.1% (19.01)	91.2% (14.31)
Avg.	90.8% (28.35)	91.0% (21.59)	93.3% (18.91)	94.7% (16.49)

(b)

Subj.	MEC	AMCC	CCA	Alg. 2
1	62.5% (18.05)	85.0% (46.10)	87.5% (50.33)	87.5% (50.33)
2	94.1% (63.32)	94.1% (63.32)	94.1% (63.32)	91.2% (57.23)
3	70.0% (25.73)	86.7% (48.94)	90.0% (54.90)	86.7% (48.94)
4	72.5% (28.62)	77.5% (34.97)	82.5% (42.14)	80.0% (38.44)
Avg.	74.8% (33.93)	85.8% (48.33)	88.5% (52.67)	86.4% (48.74)

window length, a maximum theoretical ITR of 80 bit/min can be achieved [1].

Results show that our Algorithm 2, despite its simplified approach, performs close to, or better than, MEC and AMCC methods.

It is worth noting, though, that Algorithm 2 was explicitly designed for low-electrode count setups, and does not perform any dimensionality reduction as MEC or AMCC do. However, in our scenario, where the number of electrodes is intentionally low for cost and comfort constraints, computational demand is significantly lower, as shown below. Mean ITR reported in [7], referring to MEC processing, is also comparable to our results, by taking into account the difference in the number of stimuli (5 vs. 4 from our case).

On the other hand, CCA has better accuracy and ITR than our method; in this case too, dimensionality reduction is also not taken into account in this method, and all the EEG channels are considered. Still, CCA is more computationally intensive than our algorithm: despite a thorough analysis of computational efforts goes beyond the scope of this paper, some account of computational performance is given in Table 2, which compares mean execution times of cited algorithms. Average execution times of the algorithms, on the same platform (desktop PC, Intel® Core™ i5 @ 3.20 GHz, 8 GB RAM) were extracted: meaningful performance improvement were estimated over all reference algorithms, with more marked advantages over MEC and AMCC.

This simple test, although preliminary and non-exhaustive, highlights the computational efficiency of the proposed simplified approach. Additionally, the algorithm nature is inherently more keen on firmware implementation, perspectively allowing to take full advantage of specialized digital signal processing hardware, in the framework of aimed embedded solutions.

Table 2 Comparison of mean execution time between the algorithms reported in Table 1 *(b)*.

	MEC	AMCC	CCA	Algorithm 2
Mean time	9.65 ms	5.25 ms	1.13 ms	0.82 ms
Time reduction (proposed vs. others)	-91.5 %	-84.4 %	-27.4 %	–

5. CONCLUSIONS

Two novel SSVEP signal processing algorithms were proposed and compared to most popular methods (MEC, AMCC, CCA). The algorithms were explicitly conceived to provide lightweight, calibration-less methods for SSVEP signal processing in embedded systems-oriented environments, where resource limitation and cost constraints are tighter. Preliminary tests, carried out within a Matlab environment, showed that, in a scenario employing few EEG channels, these methods can attain a fair performance, only requiring a fraction of the computational demand of reference literature methods.

Future work includes the implementation of the presented methods into embedded platforms, to provide a self-contained, autonomous BCI device. Moreover, the two presented approaches can be fused together, trading off at run time between accuracy and ITR: for example by using the faster algorithm as default, and resorting to the more accurate one just if and when the estimated error rate is too high.

6. REFERENCES

[1] J.R. Wolpaw, N. Birbaumer, D.J. McFarland, G. Pfurtscheller, T.M. Vaughan, "Brain-computer interfaces for communication and control," in *Clin. Neurophysiol.* vol.113, no.6,. pp.767-91, Jan. 2002.

[2] T. Hinterberger, S. Schmidt, N. Neumann, J. Mellinger, B. Blankertz, G. Curio, N. Birbaumer, "Brain-computer communication and slow cortical potentials," in *IEEE Trans. Biomed. Eng.*, vol.51, no.6, pp.1011-1018, Jun. 2004.

[3] G. Pfurtscheller, C. Brunner, A. Schlögl, and F. H. Lopes da Silva, "Mu rhythm (de) synchronization and EEG single-trial classification of different motor imagery tasks," in *NeuroImage* vol.31, no.1, pp.153-159, May 2006.

[4] M. Salvaris, C. Cinel, L. Citi, and R. Poli, "Novel protocols for P300-based brain-computer interfaces," in *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol.20, pp.8-17, Jan. 2012.

[5] R. Carabalona, F. Grossi, A. Tessadri, P. Castiglioni, A. Caracciolo, I. De Munari, "Light on! Real world evaluation of a P300-based brain-computer interface (BCI) for environment control in a smart home," in *Ergonomics*, vol.55, no.5, pp. 552- 563, 2012.

[6] H. Cecotti, "A Self-Paced and Calibration-Less SSVEP-Based Brain–Computer Interface Speller," in *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol.18, no.2, pp.127-133, Apr. 2010.

[7] I. Volosyak, "SSVEP-based Bremen-BCI interface - boosting information transfer rates," in *J Neural Eng.*, vol.8, no.3, Jun.2011.

[8] S. Walter, C. Quigley, S.K. Andersen, M.M. Mueller, "Effects of overt and covert attention on the steady-state visual evoked potential," in *Neurosci. Lett.*, vol.519, no.1,pp.37-41, Jun. 2012.

[9] N. Mora, V. Bianchi, I. De Munari, P. Ciampolini, "A Low Cost Brain Computer Interface Platform for AAL Applications," in *AAATE 2013 Conf. Proc.*, Sept. 19-22 Vilamoura, Portugal, 2013.

[10] N.A.M. Norani, W. Mansor, L.Y. Khuan, "A review of signal processing in brain computer interface system," in *Biom. Eng. and Sciences (IECBES), IEEE EMBS Conf. on*, pp.443,449, 2010.

[11] G. Garcia-Molina, D. Zhu, "Optimal spatial filtering for the steady state visual evoked potential: BCI application," in *Neur. Eng., 5th International IEEE/EMBS Conf. on*, pp.156,160, 2011.

[12] Z. Lin, C. Zhang, W. Wu, X. Gao, "Frequency recognition based on canonical correlation analysis for SSVEP-based BCIs," in *IEEE Trans. Biomed. Eng.*, vol.54, pp.1172–1176, Jun. 2007.