

# A SSVEP BCI BASED ON CANONICAL CORRELATION ANALYSIS

L. Talevi<sup>1</sup>, V. Mondini<sup>1</sup>, A.L. Mangia<sup>1</sup>, M. Lannocca<sup>1</sup>, A. Cappello<sup>1</sup>

<sup>1</sup> Department of Electrical, Electronic and Information Engineering (DEI), University of Bologna, Cesena, Italy

E-mail: valeria.mondini3@unibo.it

**ABSTRACT:** Canonical correlation analysis (CCA) is one of the most popular methods in the field of Brain Computer Interfaces (BCIs) based on steady-state visual evoked potentials (SSVEPs). The efficacy of the method has been widely proved, and several variations have been proposed. However, most of the approaches still consider only the first canonical correlation as a feature for classification, which can leave some important information behind. Notably, if the signal shows phase transitions, its informative content can be diffused over more than one coefficient. We show here that considering the first two canonical correlations, instead of the largest one only, can significantly improve classification accuracy without increasing computational load, and that an adjunctive pre-processing step with sinc-windowing can further enhance the results.

## INTRODUCTION

A Brain-Computer Interface (BCI) is a system creating a direct communication channel between the brain and the outside [1]. EEG-based BCIs can be based on slow cortical potentials (SCPs), event-related desynchronization/synchronization (ERD/ERS), event-related potentials (like P300), or steady-state evoked potentials (SSVEPs) [2]. Among these, SSVEP-based systems are appealing for their high accuracy and information transfer rate (ITR), due to the high signal-to-noise ratio of SSVEPs even without user training [2]. SSVEPs are periodic evoked potentials induced by repetitive visual stimulations at frequencies greater than 6Hz [3]. If two or more targets (LEDs, squares, symbols) flicker at different frequencies, an analysis of the frequency content of SSVEPs can lead to conclude which stimulus the user is gazing at.

An intuitive and commonly used frequency detection approach is the one based on *power spectral density analysis* (PSDA). In PSDA methods, power values are evaluated from the spectrum at the target stimulation frequencies, and used for classification. Recently, the application of Canonical Correlation Analysis (CCA) was proposed in the field of SSVEP BCIs [3]. The efficacy of the method has been widely proved by several studies (e.g. [4], [5]). Furthermore, its superiority to PSDA both in terms of computational load and accuracy has been shown [6], [7], so several variations of CCA have been proposed [8]–[18].

In this work, we present a SSVEP BCI based on the classical CCA method. However, we introduce here two variations in i) the pre-processing of the signals and ii) the composition of the feature vector. We show that both modifications can significantly improve classification accuracy, without an excessive increase of the computational load.

## MATERIALS AND METHODS

*EEG recording:* The EEG was recorded from 8 electrodes (PO7, PO3, O1, POz, Oz, PO4, O2, PO8) positioned according to the international 10-20 layout. The signals were acquired using the Brainbox EEG-1166 amplifier (Braintronix), with 256Hz sample frequency and a 50Hz notch filter on.

*The BCI system:* The online BCI system was implemented using LabVIEW, for a better synchronization of the signal recording and the stimulus presentation modules. SSVEP stimulation was provided through two blue LEDs, emitting lights flickering at two different frequencies,  $f_1$  and  $f_2$ . A NI MyDAQ device controlled the behavior of the LEDs, which were arranged around the screen of the PC running the software (Figure 1). We chose the LED stimulus implementation to provide accurate and stable flickering frequencies, avoiding any operating system control delay and independently from the screen refreshing rate. The implemented software was organized into three modules: *training* (T), *validation* (V) and *free mode* (F). During T and V, a yellow square appeared on the screen indicating the LED to gaze at. This permitted to deduce the true class label to train (T module), validate (V module) and use (F module) the underlying system classifier. During both T and V, the stimulus was presented in the form of subsequent trials. Each trial was composed by a *preamble*, a *stimulus* and a *break* period. During the *preamble*, the yellow square appeared near the target LED, then both lights started flickering (*stimulus*), and the trial ended with a *break* period where the squares disappeared and the LEDs shut off. No feedback was provided to the user during T module, while in V the recognized target was highlighted at the end of each trial. Both in T and V, the target sequence presentation was balanced and in random order. The *free mode* module F was designed to simulate a real operating condition. During F, both the LEDs

continuously flickered, while a square appeared near the one recognized by the classifier, as a continuous feedback for the user (Figure 1).

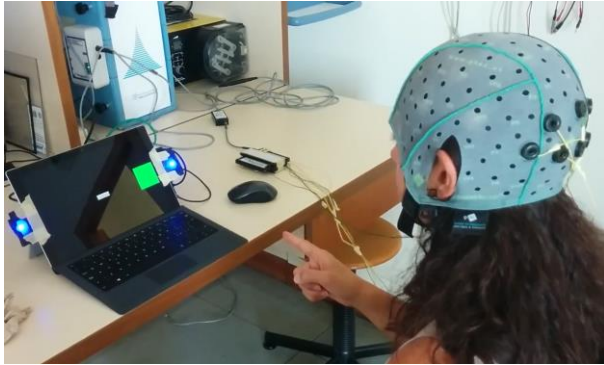


Figure 1: Operation of the system in *free mode* (F).

*Signal processing:* In all the three modules (T, V and F), 1.5s-long epochs (no overlapping) were processed by the software in three steps: i) sinc-windowing, ii) CCA analysis and iii) SVM training/classification.

First of all, the EEG segments were convolved with an adequately modulated sinc function (sinc-windowing) to perform a high-Q band-pass filtering around the two main stimulation frequencies,  $f_1$  and  $f_2$ , and  $N_{harm}$  harmonic frequencies. As it is known, the inverse Fourier transform of an ideal rectangular band-pass filter, centered on  $f_0$  and with  $M$  bandwidth, is:

$$rect\left(\frac{f-f_0}{M}\right) + rect\left(\frac{f+f_0}{M}\right) \xrightarrow{F^{-1}} 2Msinc(Mt)\cos(2\pi f_0 t) \quad (1)$$

where  $f$  is the frequency and  $F^{-1}$  is the inverse Fourier transform. Thus, the extraction of  $f_1$  and  $f_2$  components and their  $N_{harm}$  harmonics was performed with a convolution of the signals and the following function:

$$h(t) = 2Msinc(Mt) \left( \sum_{n=1}^{N_{harm}} \cos(2\pi n f_1 t) + \cos(2\pi n f_2 t) \right) \quad (2)$$

with  $M$  bandwidth and  $N_{harm}$  number of considered harmonics. A preliminary analysis suggested using  $M=2\text{Hz}$  and  $N_{harm}=3$ .

After sinc-windowing, canonical correlation analysis (CCA) was performed for feature extraction. CCA is a multivariate statistical method [19] revealing the underlying correlation between two sets of data. Notably, given two sets of variables  $\mathbf{X} \in \mathbb{R}^{p \times t}$  and  $\mathbf{Y} \in \mathbb{R}^{q \times t}$  ( $p \leq q$ ), CCA finds two corresponding sets  $\mathbf{U}=\mathbf{A}\mathbf{X}$  and  $\mathbf{V}=\mathbf{B}\mathbf{Y}$ , called *canonical variables*, so that the correlation between each pair ( $U_i, V_i$ ) is maximized:

$$\rho_i = \frac{cov(U_i, V_i)}{\sqrt{var(U_i)var(V_i)}} \quad (3)$$

while every pair ( $U_i, V_j$ ), ( $U_i, U_j$ ) and ( $V_i, V_j$ ) is uncorrelated if  $i \neq j$ . The  $p$  resulting  $\rho_i$  are called *canonical correlations*, and are a measure of similarity between the two sets of data.

The use of CCA in the field of SSVEP-based BCIs was first introduced by Lin et al [3], which proposed to perform  $k$  CCAs - one for each stimulation frequency  $f_k$  - between the set of acquired EEG signals in  $\mathbf{X}$  and a set  $\mathbf{Y}_k$  of pure SSVEP responses. Each set  $\mathbf{Y}_k$  is composed as follows:

$$\mathbf{Y}_k = \begin{pmatrix} \cos(2\pi f_k t) \\ \sin(2\pi f_k t) \\ \cos(2\pi 2f_k t) \\ \sin(2\pi 2f_k t) \\ \vdots \\ \cos(2\pi N_{harm} f_k t) \\ \sin(2\pi N_{harm} f_k t) \end{pmatrix} \quad (4)$$

with  $f_k$  stimulation frequency and  $N_{harm}$  number of considered harmonics. Even though every CCA generates multiple correlation coefficients, usually only the largest one is considered. After performing CCA between each set  $\mathbf{Y}_k$  and the recorded signals in  $\mathbf{X}$ , the segment is assigned to the frequency  $f_k$  showing the largest canonical correlation.

The efficacy of the CCA method in the SSVEP-based BCI field has been widely proved [4], [5] and many variations were proposed [8]–[18]. However, most approaches consider only the first canonical correlation as a feature for classification, which can leave some important information behind. Moreover, usually the CCA method is employed without any pre-filtering of the incoming signals (the only exceptions are [17], [18], using IIR filter banks).

In the present work, we decided to implement the standard CCA method proposed by Lin et al [3] with two slight variations: i) convolution of the signals with the above introduced sinc-windowing function (Equation 2) and ii) consideration of the two largest canonical correlations instead of the largest one only. The rationale behind this is that, if EEG shows phase transitions, the information can be diffused over more than one coefficient. We further hypothesize that, if the largest canonical correlation is mainly referred to the sine (cosine) at a certain frequency, then the second largest correlation will probably be linked to the cosine (sine) at the same frequency. We therefore decided to consider, for each frequency  $f_k$ , the square root of the sum of squares of the largest two canonical correlations:

$$r_k = \sqrt{\rho_{k1}^2 + \rho_{k2}^2} \quad (5)$$

If it is true that the second canonical correlation  $\rho_{k2}$  holds an information content complementary with respect to  $\rho_{k1}$ , then this combination of the two should incorporate a more complete information regarding the investigated frequency  $f_k$ , thus increasing the completeness of the feature and, hopefully, the achievable accuracy.

The values of  $r_1$  and  $r_2$  were extracted, for each EEG segment, from the two CCAs between  $\mathbf{X}$  and  $\mathbf{Y}_1$  and  $\mathbf{X}$  and  $\mathbf{Y}_2$ . The data were finally used to train and use a linear SVM classifier, for which we chose a soft margin parameter  $c=2$ .

*Experimental paradigm and subjects:* Four healthy volunteers (age 25 to 27, three females and a male) took part in the system test. All participants had normal or corrected to normal vision. The flickering frequencies for the two LEDs,  $f_1=12\text{Hz}$  and  $f_2=17\text{Hz}$ , were selected beforehand and were the same for all subjects. We chose these frequencies to exploit the SSVEP peak responses without harmonics overlapping. During the experiment, participants seated in a comfortable chair, approximately 60cm distant from the PC monitor.

Each volunteer underwent one *training* (T) and four *validation* (V) repetitions. Throughout the entire experiment, the system considered 1.5s-long epochs for feature extraction. Each training (T) was composed by 16 trials with 6s stimulus duration, so a total of  $16 \cdot 6 / 1.5 = 64$  elements composed the training set. Each validation (V) was composed by 24 trials with 4.5s stimulus duration, so a total of  $24 \cdot 4.5 / 1.5 = 72$  elements composed each test set.

*System evaluation:* We computed the online classification accuracy for each subject and *validation* repetition. To evaluate the influence of the two proposed variations (sinc-windowing and feature composition) on classification accuracy, all data were re-analyzed to test all the possible combinations. We therefore tested our method against i) sinc-windowing + CCA with classical feature extraction (first canonical correlation) ii) no sinc windowing and CCA with the proposed feature extraction and iii) no sinc-windowing and CCA with classical feature extraction.

Just for the sake of comparison, we repeated simulations also with a PSDA-based method. In this case, we composed the feature vector by using the periodogram-estimated powers in 2Hz-large bins around  $f_1, f_2$  and  $N_{\text{harm}}$  respective harmonics.

Each accuracy was compared to chance level [20] via confidence intervals ( $\alpha=0.05$ ). As regards the comparisons between methods, to account for the fact that multiple data came from the same subject (i.e. the samples could not be assumed to be completely independent), we ran the evaluations as post-hoc tests of a repeated measures ANOVA. The ANOVA design included both the factors “method” (the within-subject factor) and “subject”, thus considering all dependencies among data. The post-hoc analyses were performed through Fisher’s LSD. A preliminary Kolmogorov-Smirnov test confirmed the normality of data distributions, which justified the use of parametric statistical tests.

The computation times for the presented procedure and PSDA were also evaluated and compared through a paired t-test, and the proportion of time required for sinc-windowing was further investigated.

The average and peak information transfer rate (ITR) [21] were finally computed according to:

$$ITR(\text{bit}/\text{min}) = \frac{60}{T} \left( \log_2(N) + p \log_2(p) + (1-p) \log_2 \left( \frac{1-p}{N-1} \right) \right) \quad (6)$$

where  $N=2$  is the number of choices,  $p$  is classification accuracy and  $T$  is the epoch duration (1.5s).

## RESULTS

The classification accuracies obtained for the five methods are detailed in Table 1 for each subject and *validation* repetition, and summarized in Figure 2. The chance level at  $\alpha=0.05$  for our experimental setup was 61.25%, so all the obtained accuracies were significantly higher than chance, with the only exception of PSDA. The results of the post-hoc comparisons between each pair of methods are detailed in Table 2.

Table 1: Detailed accuracies (each subject and validation repetition) for the five methods.

		sinc+CCA (sumsq)	sinc+CCA (first)	only CCA (sumsq)	only CCA (first)	PSDA
S1	val <sub>1</sub>	97.2	97.2	94.4	94.4	77.8
	val <sub>2</sub>	95.8	91.6	94.4	91.6	76.4
	val <sub>3</sub>	98.6	98.6	97.2	97.2	88.9
	val <sub>4</sub>	100	100	98.6	93.1	87.5
S2	val <sub>1</sub>	88.9	84.7	91.7	84.7	70.8
	val <sub>2</sub>	87.5	79.2	83.3	80.6	65.3
	val <sub>3</sub>	80.6	75.0	72.2	68.1	47.2
	val <sub>4</sub>	94.4	94.4	93.1	90.3	68.1
S3	val <sub>1</sub>	87.5	84.7	81.9	81.9	69.4
	val <sub>2</sub>	86.1	83.3	86.1	83.3	66.7
	val <sub>3</sub>	93.1	90.3	93.1	87.5	61.1
	val <sub>4</sub>	86.1	88.9	86.1	80.6	59.7
S4	val <sub>1</sub>	81.9	76.4	72.2	69.4	63.9
	val <sub>2</sub>	75.0	75.0	79.2	77.8	65.3
	val <sub>3</sub>	84.7	80.6	86.1	79.2	66.7
	val <sub>4</sub>	80.6	80.6	80.6	76.4	69.4
<b>Average</b>		<b>88.6</b>	<b>86.3</b>	<b>86.9</b>	<b>83.5</b>	<b>69.0</b>
<b>Peak</b>		<b>100</b>	<b>100</b>	<b>98.6</b>	<b>97.2</b>	<b>88.9</b>

Table 2: p-values from the post-hoc tests between each pair of methods.

	sinc+CCA (sumsq)	sinc+CCA (first)	only CCA (sumsq)	only CCA (first)	PSDA
sinc+CCA (sumsq)	-	p<0.01 **	p=0.11	p<0.001 ***	p<0.001 ***
sinc+ CCA (first)	-	-	p=0.53	p<0.01 **	p<0.001 ***
only CCA (sumsq)	-	-	-	p<0.001 ***	p<0.001 ***
only CCA (first)	-	-	-	-	p<0.001 ***

The implemented method performed significantly ( $p < 0.001$ ) better with respect to standard CCA method with no sinc-windowing. The accuracy improvement occurred indeed in almost every subject and session, with an average improvement of 5.1% and a peak improvement of 12.5%. As regards the influence of the single factors we can observe that the consideration of the first two canonical variables significantly outperforms the consideration of the largest only, both in the sinc-windowing ( $p < 0.01$ ) and no-sinc-windowing ( $p < 0.001$ ) condition. As regards the PSDA method, this confirmed to perform significantly worse ( $p < 0.001$ ) than any CCA variation.

As regards computation times, our CCA-based method confirmed to be significantly ( $p < 0.001$ ) faster with respect to PSDA, with an average time per operation of approximately the half ( $110\mu\text{s}$  against  $239\mu\text{s}$ ). As concerns sinc-windowing, it contributed for approximately a third on average ( $35\mu\text{s}$ ) with respect to the total time of each operation ( $110\mu\text{s}$ ).

As regards the information transfer rate of the presented system, we obtained a peak ITR of 40bits/min and an average ITR of 20.12bits/min. We don't detail the ITRs for each subject and *validation* to avoid repetition, but they can be easily computed from Table 1.

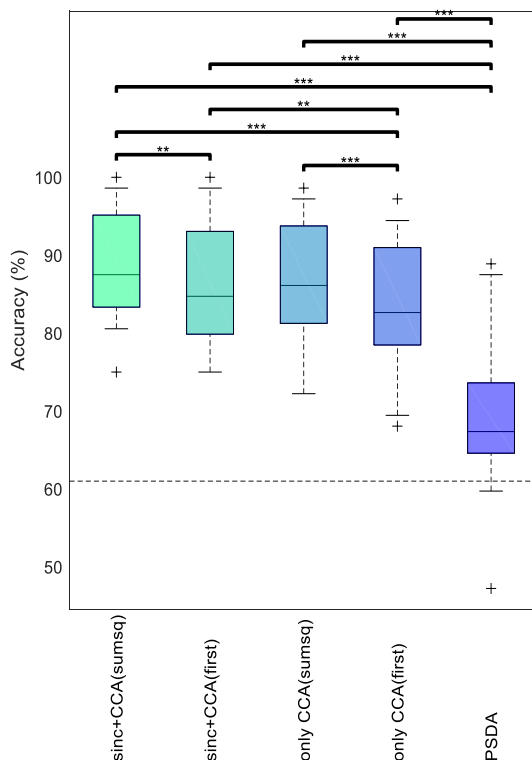


Figure 2: A box-plot showing the classification accuracy distributions for the five methods. The double star \*\* indicates a  $p$ -value  $< 0.01$ , while triple star \*\*\* a  $p$ -value  $< 0.001$ . The horizontal, dashed line marks the chance level ( $\alpha = 0.05$ ).

## DISCUSSION

Our results show how the consideration of two canonical correlations instead of using the largest one only, significantly improves the achievable accuracy without increasing computational load. The described effect is probably due to the fact that, since the canonical variables  $U_i$  are uncorrelated, the second canonical variable  $U_2$  will contain information which are in quadrature with those contained in the first canonical variable  $U_1$ . So, if  $U_1$  is mainly explained e.g. by the sine at a certain frequency, then  $U_2$  will be mainly explained by the cosine at the same frequency. Then, taking the previously described combination of the largest correlations will include a more complete information.

Although Table 1 and 2 suggest that the consideration of two canonical correlations improves the performances regardless of sinc-windowing, we still retain that a pre-processing step is important. We indeed hypothesize that the positive influence of sinc-windowing may emerge depending on both the subject and the set of stimulation frequencies. To give an example, if a subject showed an enhanced peak near one of the stimulation frequencies, independently from the stimulation condition (e.g. if the subject showed an enhanced spontaneous alpha rhythm and one of the selected frequencies was in the alpha range), then the adjunctive role of a narrow-band filtering would be enhanced. Since sinc-windowing only affects the total computation time for approximately one third, we think it is reasonable to keep and recommend this feature in future implementations. However, further data are required to confirm the importance of its role.

As regards the comparison with PSDA, our results confirm the ones in literature [6], [7], which indicate the superiority of CCA both in terms of accuracy and computational load.

As regards the performances of our system in absolute terms, it is difficult to compare ITRs because most of the recent studies implement more than 2 classes, which drastically increases ITR. The most recent 2-class BCI based on SSVEPs found in literature is the one in [22], which reports a *peak* accuracy of 89.9% and a *peak* ITR of 10.30bits/min. Since our *average* accuracy and ITR were of 88.6% and 20.12bits/min, we think we can say our results are at least in line with the reported ones. A multi-class implementation of the presented paradigm could lead to an improvement in ITRs too.

## CONCLUSION

In the present work we implemented a 2-class SSVEP-based BCI system. The system was based on CCA analysis, and our results indicate that considering two canonical correlations instead of the largest one only can significantly improve accuracy without increasing the computational load. An additional narrow-band filtering permits to gain an average 5.1% and a peak of 12.5% accuracy with respect to classical CCA. Even though this is only a 2-class paradigm, it can be easily extended to multi-class to improve ITR. An advantage of the

presented system is that it remains quite simple, light and fast, since it only performs sinc-windowing of the incoming signals, followed by a CCA feature extraction and SVM classification. We think taking low computational costs and simple procedures is an important aspect, especially to favor the spread of low-cost and high-portability devices.

## REFERENCES

- [1] L. F. Nicolas-Alonso e J. Gomez-Gil, «Brain Computer Interfaces, a Review», *Sensors*, vol. 12, n. 2, pagg. 1211–1279, gen. 2012.
- [2] S. Amiri, A. Rabbi, L. Azinfar, e R. Fazel-Rezai, «A review of P300, SSVEP, and hybrid P300/SSVEP brain-computer interface systems,[w:] Brain-Computer Interface Systems–Recent Progress and Future Prospects, 2013», *DOI*, vol. 10, pag. 56135.
- [3] Z. Lin, C. Zhang, W. Wu, e X. Gao, «Frequency recognition based on canonical correlation analysis for SSVEP-based BCIs», *IEEE Trans. Biomed. Eng.*, vol. 54, n. 6, pagg. 1172–1176, 2007.
- [4] G. Bin, X. Gao, Z. Yan, B. Hong, e S. Gao, «An online multi-channel SSVEP-based brain–computer interface using a canonical correlation analysis method», *J. Neural Eng.*, vol. 6, n. 4, pag. 046002, 2009.
- [5] Y. Zhang, P. Xu, T. Liu, J. Hu, R. Zhang, e D. Yao, «Multiple Frequencies Sequential Coding for SSVEP-Based Brain-Computer Interface», *PLOS ONE*, vol. 7, n. 3, pag. e29519, mar. 2012.
- [6] Q. Wei, M. Xiao, e Z. Lu, «A comparative study of canonical correlation analysis and power spectral density analysis for ssvp detection», in *Intelligent Human-Machine Systems and Cybernetics (IHMSC), 2011 International Conference on*, 2011, vol. 2, pagg. 7–10.
- [7] G. Hakvoort, B. Reuderink, e M. Obbink, «Comparison of PSDA and CCA detection methods in a SSVEP-based BCI-system», 2011.
- [8] Y. Zhang *et al.*, «Multiway Canonical Correlation Analysis for Frequency Components Recognition in SSVEP-Based BCIs», in *Neural Information Processing*, 2011, pagg. 287–295.
- [9] J. Pan, X. Gao, F. Duan, Z. Yan, e S. Gao, «Enhancing the classification accuracy of steady-state visual evoked potential-based brain–computer interfaces using phase constrained canonical correlation analysis», *J. Neural Eng.*, vol. 8, n. 3, pag. 036027, 2011.
- [10] Y. Zhang, G. Zhou, J. Jin, M. Wang, X. Wang, e A. Cichocki, «L1-Regularized Multiway Canonical Correlation Analysis for SSVEP-Based BCI», *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 21, n. 6, pagg. 887–896, nov. 2013.
- [11] M. H. Chang e K. S. Park, «Frequency recognition methods for dual-frequency SSVEP based brain-computer interface», in *Engineering in Medicine and Biology Society (EMBC), 2013 35th Annual International Conference of the IEEE*, 2013, pagg. 2220–2223.
- [12] Y. U. Zhang, G. Zhou, J. Jin, X. Wang, e A. Cichocki, «Frequency recognition in SSVEP-based BCI using multiset canonical correlation analysis», *Int. J. Neural Syst.*, vol. 24, n. 04, pag. 1450013, 2014.
- [13] M. Nakanishi, Y. Wang, Y.-T. Wang, Y. Mitsukura, e T.-P. Jung, «Enhancing unsupervised canonical correlation analysis-based frequency detection of SSVEPs by incorporating background EEG», in *Engineering in Medicine and Biology Society (EMBC), 2014 36th Annual International Conference of the IEEE*, 2014, pagg. 3053–3056.
- [14] Y. Wang, M. Nakanishi, Y.-T. Wang, e T.-P. Jung, «Enhancing detection of steady-state visual evoked potentials using individual training data», in *Engineering in Medicine and Biology Society (EMBC), 2014 36th Annual International Conference of the IEEE*, 2014, pagg. 3037–3040.
- [15] Y. Zhang, G. Zhou, J. Jin, X. Wang, e A. Cichocki, «SSVEP recognition using common feature analysis in brain–computer interface», *J. Neurosci. Methods*, vol. 244, pagg. 8–15, apr. 2015.
- [16] P. Yuan, X. Chen, Y. Wang, X. Gao, e S. Gao, «Enhancing performances of SSVEP-based brain–computer interfaces via exploiting inter-subject information», *J. Neural Eng.*, vol. 12, n. 4, pag. 046006, 2015.
- [17] X. Chen, Y. Wang, S. Gao, T.-P. Jung, e X. Gao, «Filter bank canonical correlation analysis for implementing a high-speed SSVEP-based brain–computer interface», *J. Neural Eng.*, vol. 12, n. 4, pag. 046008, 2015.
- [18] M. R. Islam, T. Tanaka, M. Nakanishi, e M. K. I. Molla, «Frequency recognition of steady-state visually evoked potentials using binary subband canonical correlation analysis with reduced dimension of reference signals», in *Acoustics, Speech and Signal Processing (ICASSP), 2016 IEEE International Conference on*, 2016, pagg. 769–773.
- [19] H. Hotelling, «Relations between two sets of variates», *Biometrika*, vol. 28, n. 3/4, pagg. 321–377, 1936.
- [20] G. Mueller-Putz, R. Scherer, C. Brunner, R. Leeb, e G. Pfurtscheller, «Better than random: A closer look on BCI results.», *Int. J. Bioelectromagn.*, vol. 10, n. EPFL-ARTICLE-164768, pagg. 52–55, 2008.
- [21] P. Yuan, X. Gao, B. Allison, Y. Wang, G. Bin, e S. Gao, «A study of the existing problems of estimating the information transfer rate in online brain–computer interfaces», *J. Neural Eng.*, vol. 10, n. 2, pag. 026014, 2013.
- [22] E. C. Lalor *et al.*, «Steady-state VEP-based brain-computer interface control in an immersive 3D gaming environment», *EURASIP J. Appl. Signal Process.*, vol. 2005, pagg. 3156–3164, 2005.