TOWARDS A COMPRESSIVE SENSING-BASED SSVEP-BCI

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Abstract— In this research, a study of SSVEP frequency detection is carried out for its application in compressive sensing (CS)-based brain-computer interface (BCI). The CS-BCI system is based on compressing electroencephalogram (EEG) signals using random projection, transmitting the compressed data using wireless method, and reconstructing EEG signals from the received data using a CS-reconstruction algorithm. Minimum Energy Combination (MEC), Canonical Correlation Analysis (CCA) and Multivariate Synchronization Index (MSI) algorithms are applied for the detection of visual stimulus frequency from the reconstructed EEG signals. For CS-reconstruction, the ℓ_p^d-regularized least-squares ($\ell_p^d - \text{RLS}$), ℓ_p^{2d}-regularized least-squares ($\ell_p^{2d} - \text{RLS}$), and the block-sparse Bayesian learning bound-optimization ($\text{BSBL} - \text{BO}$) algorithms are applied. Results of simulation conducted using EEG signals acquired by using Emotiv headset indicate that the MSI algorithm offers the highest mean classification accuracy (CA), whereas the CCA algorithm offers the most stable CA. Also, the $\ell_p^d - \text{RLS}$ algorithm is found to balance the trade-off between the high mean value of CA offered by the $\text{BSBL} - \text{BO}$ algorithm and the most stable value of CA offered by the $\ell_p^{2d} - \text{RLS}$ algorithm.

Keywords— Compressive Sensing, SSVEP-BCI, CCA, MSI, MEC.

Resumo— No presente trabalho, um estudo relacionado à detecção de frequências através de potencias visualmente evocados foi executado após um processo de compressão usando a teoria denominada *Compressive Sensing* (CS). Para este estudo, a teoria de CS foi aplicada a Interfaces Cérebro Computador (BCI). O sistema de CS-BCI implementado utiliza sinais de Eletroencefalografia (EEG) processadas através de projeções randómicas. Após este processo, os dados foram transmitidos sem fio e reconstruídos através de algoritmos de reconstrução de CS. Os algoritmos de extração de características, tais como Energia Mínima de Combinação (EMC), Análise de Correlação Canónica (CCA) e Índice de Sincronização Multivariável (MSI), foram aplicados na detecção das frequências a partir dos sinais de EEG reconstruídas. Na etapa de reconstrução foram aplicados os seguintes algoritmos: ℓ_p^d-mínimos quadrados regularizados ($\ell_p^d - \text{RLS}$), ℓ_p^{2d}-mínimos quadrados regularizados ($\ell_p^{2d} - \text{RLS}$) e Aprendizagem Bayesiana ligada à otimização por bloco-dispersão ($\text{BSBL} - \text{BO}$). Os resultados de simulação, a partir dos sinais de EEG coletados pelo dispositivo sem fio Emotiv-Epoc, mostram que o algoritmo de MSI oferece as mais altas taxas de precisão. Por outra parte, o algoritmo de CCA mostrou os resultados mais estáveis. Finalmente, o algoritmo $\ell_p^d - \text{RLS}$ apresentou um resultado médio que equilibra os altos valores oferecidos pelo algoritmo $\text{BSBL} - \text{BO}$ e o valor mais estável de classificação resultante do algoritmo ℓ_p^{2d}-regularized least-squares ($\ell_p^{2d} - \text{RLS}$).

Palavras-chave— Teoria de compressão, SSVEP-BCI, CCA, MSI, MEC.

1 Introduction

In a BCI based on Steady-State Visual Evoked Potentials (SSVEPs), suitable commands to control machine functions are generated by focusing gaze on one of several stimuli flickering with different frequencies. Therefore, when the eye retina is excited by a stimulus at a certain frequency, the brain generates an electrical activity of the same frequency with its harmonics. This traditional SSVEP-BCI, also widely named as "dependent" SSVEP-BCI, might not be applicable for patients with ocular motor impairments or severe neuromuscular problems. Nonetheless, "independent" SSVEP-BCIs can address this problem through the power of the attention in flickering targets and the human visual selectivity in spaces reduced (Details about definitions of an Independent SSVEP-BCI can be reviewed in (Tello et al., 2016)). The effects of spatial attention on SSVEP were studied initially in (Morgan et al., 1996). In the work performed by (Kelly et al., 2004), it was shown that there was a reduction in 20% of precision when a volunteer did not perform eye movements compared to another who did it. In (Kelly et al., 2005), something similar was performed using flickering letters in a CRT monitor. Six out of eleven physically and neurologically healthy subjects demonstrate reliable control in binary decision-making, achieving at least 75% of correct selections. Several attempts have been made to understand more about SSVEPs, which is discussed in (Tello et al., 2014).

SSVEP-BCI sensors are desired to be comfortable and portable (Hairston et al., 2014). The conductive Ag/AgCl gel-based electrodes, which are popular in wired BCI systems, could be replaced by wireless acquisition devices with saline-based wet-contact resistive electrodes or dry active electrodes. On the other hand, Compressive Sensing (CS) is emerging as a promising technique for the development of low-power, small-chip, and robust wireless BCI sensors (Pant and Krishnan, 2014; Zhang et al., 2013). It is shown that the use of a sparse measurement matrix and a reconstruction algorithm based on promoting temporal correlation can offer improved reconstruction performance for CS of certain physiological signals. In (Tello, Pant, Müller, Krishnan and Bastos-Filho, 2015), we applied CS on the EEG database obtained by using BrainNet-36, which acquires reliable EEG signals by using wired electrodes. It is found that the MSI algorithm can offer better performance relative to CCA algorithm.

In this study, it was carried out an analysis of the MEC, CCA, and MSI algorithms, which are popular for the detection of visual stimulus frequency in SSVEP-BCI systems, and the ℓ_p^d-RLS, $\ell_p^{2d}-$RLS, and BSBL $-$ BO algorithms, which are popular for the reconstruction of physiological signals, for a CS-based SSVEP-BCI system. Emotiv Epoc, a comfortable and portable wireless EEG sensing device, is used for the acquisition of EEG signals from the occipital region of the brain. The block diagram of the studied SSVEP-BCI system is shown in Figure 1. The key blocks in Figure 1 are discussed below.

2 Wireless EEG Acquisition

Emotiv Epoc Headset is a wireless device used for acquiring signal. EEG signals from occipital O1 and O2 channels with 128 samples per second of sampling rate (f_s) were collected. The sensors used for reference are: (i) Common-Mode Sensing (CMS) and, (ii) Driven Right Leg (DRL) that are fixed for default and in parallel to P3/P4 channels (the two mastoids), respectively.

3 Compression

CS used for signal compression, which involves segmenting EEG signals into non-overlapping segments $\{\boldsymbol{x}_i\}$, and applying the operation

$$\boldsymbol{y} = \boldsymbol{\Phi x} \tag{1}$$

where vector $\boldsymbol{x}$ of length N representing a signal and its measurement vector $\boldsymbol{y}$ of length M. $\boldsymbol{\Phi}$ is a sparse matrix of size $M \times N$ with 5 number of unity valued nonzero components in each column, where $M \ll N$.

4 Reconstruction

Signal reconstruction is carried out by using the ℓ_p^d $-$ RLS, ℓ_p^{2d} $-$ RLS, and BSBL $-$ BO algorithms (Pant and Krishnan, 2014; Pant and Krishnan, 2013; Zhang and Rao, 2013). The ℓ_p^d $-$ RLS and $\ell_p^{2d}-$RLS algorithms are based on solving the optimization problem

$$\underset{\boldsymbol{x}}{\text{minimize}} \frac{1}{2} \left|\left|\boldsymbol{\Phi x} - \boldsymbol{y}\right|\right|_2^2 + \lambda f(\boldsymbol{x}), \text{with} \tag{2}$$

the minimization of

$$\left\|\boldsymbol{x}^d\right\|_p = \left(\sum_{n=1}^{N-1} |x_n - x_{n+1}|^p\right)^{1/p} \quad \text{and} \tag{3}$$

$$\left\|\boldsymbol{x}^{2d}\right\|_p = \left(|x_1 - x_2|^p + \sum_{n=1}^{N-1} |x_{n-1} - 2x_n + x_{n+1}|^p + |x_{n-1} - x_n|^p\right)^{1/p} \tag{4}$$

respectively, with $\lambda > 0$. The BSBL $-$ BO algorithm divides signal $\boldsymbol{x}$ in to signal blocks $\overrightarrow{\boldsymbol{x}_1}, \overrightarrow{\boldsymbol{x}_2}, \cdots, \overrightarrow{\boldsymbol{x}_s}$ as $\boldsymbol{x} = \left[\overrightarrow{\boldsymbol{x}_1}, \overrightarrow{\boldsymbol{x}_2}, \cdots, \overrightarrow{\boldsymbol{x}_s}\right]^T$, and signal $\boldsymbol{x}$ is estimated as

$$\boldsymbol{x} = \sum\nolimits_0 \Phi^T (\lambda I + \Phi \sum\nolimits_0 \Phi^T)^{-1} \boldsymbol{y} \tag{5}$$

where $\sum_0 = diag\{\gamma_1 \mathbf{B}_1, \gamma_2 \mathbf{B}_2, \cdots, \gamma_s \mathbf{B}_s\}$ and parameters γ_i and $\mathbf{B}_i$ control block-sparsity and correlation structure, respectively, see (Pant and Krishnan, 2014) and (Zhang and Rao, 2013) for details.

5 Minimum Energy Combination

MEC is a technique of finding combinations of electrode signals that remove strong noise and nuisance signals from EEG data (Friman et al., 2007). For SSVEP data stimulated by the frequency f_i (i represents the number of targets), the response can be modeled by adding noise. X is the EEG signal, and Y_i is the reference signal. The signals (from O1 and O2) are combined to extract the discriminative features. This combination can be achieved by linear transformation of X. The class was determined through a criterion of maxima. More details can be seen at (Tello et al., 2014).

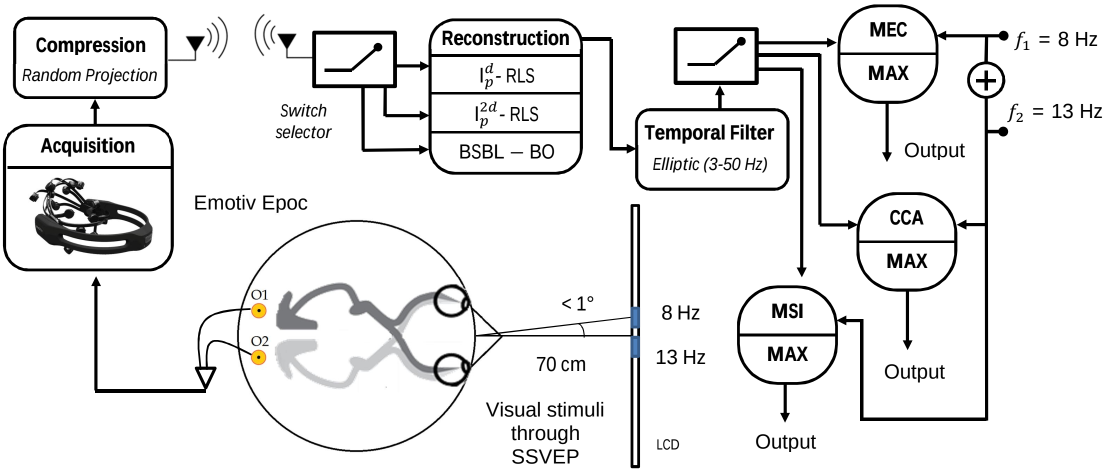

Figure 1: Block diagram of the proposed SSVEP-BCI system.

6 Canonical Correlation Analysis

CCA is a widely used technique in the processing of EEG signals based on the detection of SSVEP components for multichannels (Lin et al., 2007). Mathematically, this method assumes that X represents discrete-time signal segments, and Y_i consists of simulated stimulus signals. Thus, a total of H harmonic sine vectors and cosine vectors for frequency f_i, all of length L were modeled. We have considered the fundamental frequency and one harmonic as the simulated frequency generator, i. e. $H = 2$. More details about this approach is detailed in (Tello et al., 2014). Finally, the process of correlation of these signals is executed and the classes obtained through a criterion of maxima.

7 Multivariate Synchronization Index

MSI is a method to estimate the synchronization between the actual mixed signals and the reference signals as a potential index for recognizing the stimulus frequency. In (Zhang et al., 2014), the use of a S-estimator as index is proposed, which is based on the entropy of the normalized eigenvalues of the correlation matrix of multivariate signals. Autocorrelation matrices $\mathbf{C}_{11}$ and $\mathbf{C}_{22}$ for $\mathbf{X}$ and $\mathbf{Y}_i$, respectively, and cross-correlation matrices $\mathbf{C}_{12}$ and $\mathbf{C}_{21}$ were changed from the original version (Zhang et al., 2014) due to its inconsistency in the dimensions of each component for the formation of the correlation matrix $\mathbf{C}^i$ (more details are described on (Tello et al., 2014; Tello, Müller, Ferreira and Bastos, 2015; Tello et al., 2016)). Finally, the class was obtained through a criterion of maxima.

$$\mathbf{C}_{11} = (1/M).\mathbf{X}\mathbf{X}^T, \tag{6}$$

$$\mathbf{C}_{22} = (1/M).\mathbf{Y}_i\mathbf{Y}_i{}^T, \tag{7}$$

$$\mathbf{C}_{12} = (1/M).\mathbf{X}\mathbf{Y}_i{}^T, \tag{8}$$

$$\mathbf{C}_{21} = (1/M).\mathbf{Y}_i\mathbf{X}^T, \tag{9}$$

8 Visual Stimuli

Each volunteer was sitting in a comfortable chair, in front of a 17-inch LCD monitor, and 70 cm away from it. Two stimuli based on checkerboards (4×4) were simultaneously presented in bilateral way. These stimuli were generated by a subsystem based on FPGA (Field-Programmable Gate Array) Xilinx Spartan 3E company. The stimuli were placed by side along a horizontal line separated by a small distance (≈2cm) where the left and right target were flickered at the rate of $f_1 = 8$ Hz (left) and $f_2 = 13$ Hz (right), respectively. More details about the stimuli are shown in (Tello, Pant, Müller, Krishnan and Bastos-Filho, 2015).

9 Subjects and Experimental Procedure

Three male subjects participated in the study (Mean: 29.7 and SD: 0.58). The experiments were performed in accordance with the rules of the Ethics Committee of the Federal University of Espirito Santo (UFES/Brazil), with the registration N^o CEP-048/08. During the first five seconds, a fixed cross in the center of the screen is presented. After finalizing the first five seconds, a beep indicates to the volunteer to fix his/her attention on the left side of the stimulus for thirty seconds. At the end of this time, the volunteer has five seconds to take rest and another thirty seconds is asked to pay attention in stimulating the right side. The time of duration of the experiment is 70 seconds. The eye movements are also monitored and there has been suggested keep a maximum visual angle of 1^o for the stimulus selection.

10 Experimental results

Initially, signals from O1 and O2 channels were extracted. Then, a compression stage of 75% of ratio was applied. In brief words, the signals were transmitted and then reconstructed. Thus, a signal-vector of length 42000 samples (70 seconds time f_s) was divided into total 42 non-overlapping segments each of length $Q = 1000$. A matrix w of size $Q \times 42$ was constructed by including the 42 segments as its columns. One value of the number of measurements was selected as $P = 250$, which correspond to compression ratio ($CR = 75\%$), where CR was computed as $(Q - P) \times 100/Q\%$. The $\ell_p^{2d} - \mathrm{RLS}$, $\ell_p^{d} - \mathrm{RLS}$, and $\mathrm{BSBL} - \mathrm{BO}$ algorithms were applied to reconstruct signal segments from each of the 42 columns of Y_i. The $\ell_p^{2d} - \mathrm{RLS}$ algorithm was applied with parameters $p = 1$, $T = 30$, $\lambda_1 = 1$, $\lambda_T = 10^{-2}$, $\epsilon_1 = 1$, $\epsilon_T = 10^{-2}$ and the $\mathrm{BSBL} - \mathrm{BO}$ algorithm was applied with parameters such as in (Pant and Krishnan, 2014) with the discrete-cosine transform basis. The segments were reconstructed by applying the three algorithms and concatenated to construct three reconstructed versions of the signal $\boldsymbol{x}$. In the preprocessing stage, the data were segmented and windowed with window lengths (WL) of 1 s and 4 s, each one with an overlap of 50%. Then, a temporal elliptic filter between 3-50 Hz was applied. The MEC, CCA and MSI techniques were applied and the results were compared in terms of performance. The comparison of performance (mean and standard deviation) was tested in 50 repetitions of reconstructed EEG signals averaged for the 3 subjects in different WL as shown in Fig 2. In addition, these results were also compared with the original EEG signal for each case. A summary of the results are shown in Table 1.

11 Conclusion and discussion

An analysis of the MEC, CCA, and MSI algorithms for the detection of visual stimulus frequency in SSVEP-BCI systems was carried out. The analysis was done for the application in CS-based wireless BCI system. The ℓ_p^d-RLS, ℓ_p^{2d}-RLS, and $\mathrm{BSBL} - \mathrm{BO}$ algorithms were applied for the reconstruction of signals from compressed data. The MEC, CCA, and MSI algorithms were applied for the detection of visual stimulus frequency from reconstructed EEG signals. According to the obtained results, the MEC algorithm was found to offer the better trade-off between the highest mean value of CA offered by the MSI algorithm and the lowest variance of the CA offered by the CCA algorithm (evidences that this modified version of MSI show good results were also found in (Tello et al., 2014; Tello, Bissoli, Ferrara, Müller, Ferreira and Bastos, 2015; Tello, Valadao and Bastos-Filho, 2015)). The $\ell_p^d - \mathrm{RLS}$ algorithm was also found to balance the trade-off between the highest mean and lowest variance of CA offered by the $\mathrm{BSBL} - \mathrm{BO}$ algorithm and the lowest mean and highest variance of CA offered by the $\ell_p^{2d} - \mathrm{RLS}$ algorithm. Also, the increase in the length of EEG signal is found to increase not only the mean value of CA but also the variance of CA.

Table 1: Summary results related to Mean (μ) and Variance(σ) in [%]

WL	ℓ_p^d	ℓ_p^{2d}	BSBL-BO	WL	ℓ_p^d	ℓ_p^{2d}	BSBL-BO
1 s	**Mean (μ)**			4 s	**Mean (μ)**		
MEC	56.96	56.57	59.73	MEC	62.64	61.16	65.31
CCA	50.79	50.27	53.68	CCA	51.24	50.64	55.21
MSI	55.51	51.36	61.86	MSI	64.23	54.26	69.90
1 s	**Variance (σ)**			4 s	**Variance (σ)**		
MEC	8.28	7.48	8.77	MEC	13.09	12.43	11.97
CCA	1.99	1.08	4.27	CCA	3.46	2.22	7.20
MSI	5.52	1.86	9.95	MSI	13.68	5.47	13.89

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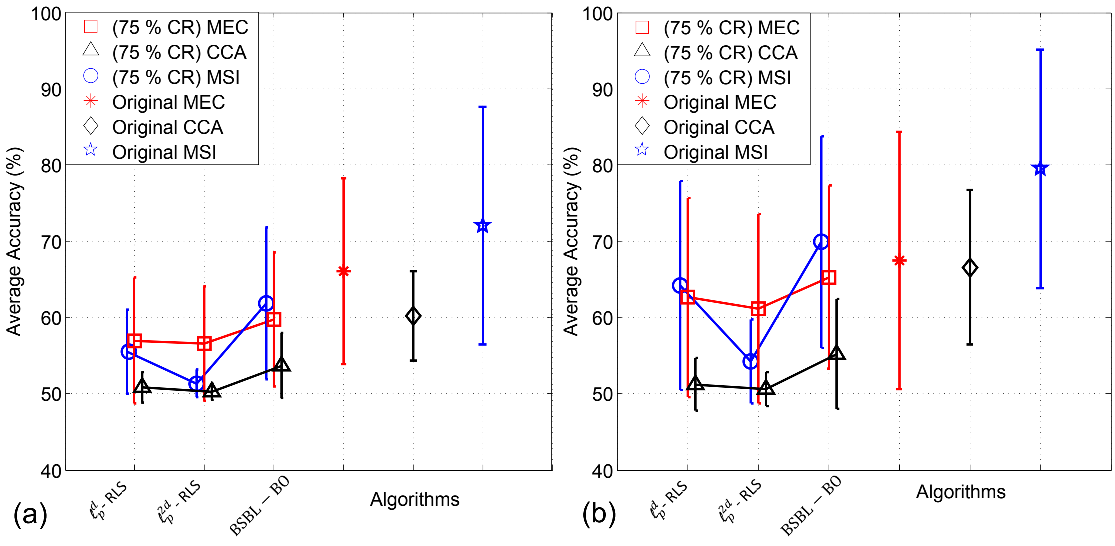

Figure 2: (a) Average of accuracy with window length of 1s and (b) 4s, respectively.

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