PERFORMANCE IMPROVEMENTS FOR NAVIGATION OF A ROBOTIC WHEELCHAIR BASED ON SSVEP-BCI

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Abstract—In this work, we present the development by stages of a robotic wheelchair commanded by a Brain Computer Interface based on Steady State Visual Evoked Potentials (SSVEP-BCI). A comparison of performance in classifying trajectories using three feature extractors to recognize SSVEPs were evaluated. These methods are: Minimum Energy Combination (MEC), Canonical Correlation Analysis (CCA) and Multivariate Synchronization Index (MSI). Three subjects participated of the experiments and Electroencephalogram (EEG) signals were captured through a wired biosignal acquisition system named BrainNet-36. Four frequencies were used as stimuli and each target represents a specific action or class: 8.0 Hz (turn left), 11.0 Hz (forward), 13.0 Hz (turn right) and 15.0 Hz (stop). According to our results of classification, MSI technique achieved the highest values of accuracy with a mean of 88.00 % using window length of 1 s. Moreover, it was confirmed that a modified version of MSI technique should be the most stable due to its low Standard Deviation (SD) (2.00). Furthermore, related to the executed trajectories, MSI technique performed a similar path to the desired trajectory. Our main goal is to achieve a robust, accurate, efficient and functional SSVEP-BCI applied to a robotic wheelchair that can navigate in an established path or in a fully automatic unsupervised environment.

Keywords—SSVEP-BCI, Robotic Wheelchair, MEC, CCA, MSI.

1 Introduction

Brain-computer interface (BCI) is a technology which provides to human a direct communication between the user’s brain signals and a computer, generating an alternative channel of communication that does not involve the traditional way as muscles and nerves (Wolpaw J.R., 2000). Therefore, a BCI records brain signals and extracts Electroencephalography (EEG) signal features and these features are then translated into artificial outputs or commands that act in a real world. BCI promises to be a potential alternative and augmentative communication (AAC) and control solution for people with severe motor disabilities (Kelly et al., 2005).

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 multiples or harmonics. This stimulus produces a stable Visual Evoked Potential (VEP) of small amplitude termed as “Steady-State” Visually Evoked Potentials (SSVEPs) of the human visual system. Thus, the main idea of a traditional SSVEP-BCI is activating commands through control of gaze where several stimuli flicker at different frequencies and where each flicker represents a command. According to Regan (Wu et al., 2008), a flickering stimulus of different frequency with a constant intensity can evoke SSVEPs with a maximum amplitude in low (5-12 Hz), medium (12-25 Hz) and high (25-50 Hz) frequency bands, separately.

In the context of smart environments applied to assistive technologies, people with different lev-
els of disabilities have the ability to control devices from their biological signals without the need of movements of hands or/and legs. A previous work involving a robotic wheelchair and SSVEP signals from our research group was reported in (Bastos et al., 2011).

This work presents a robotic wheelchair that can be commanded by users using a SSVEP-BCI in an established path or by a fully automatic unsupervised navigation system. Also, this study attempts to compare the performance of algorithms to SSVEPs recognition, such as MEC, CCA and MSI, in classifying trajectories in a defined path with aim of getting a robust, accurate, efficient and functional SSVEP-BCI applied to a robotic wheelchair. A graphical explanation of the process is illustrated in Figure 1.

2 Theoretical Background

2.1 Minimum Energy Combination (MEC)

MEC is a technique of finding combinations of electrode signals that remove strong noise and nuisance signals for EEG data (Friman et al., 2007). MEC is based on PCA (Zhang et al., 2014). For SSVEP data stimulated by a specific frequency \( f_i \), the response can be modeled adding the noise as follows:

\[
X^T = Y^T A + E
\]

where \( X \) is the EEG signal, and \( Y \) is the reference signal. \( A \) is the amplitude matrix of size \( 2H \times N \) for all electrode signals, \( H \) is the number of harmonics evaluated and \( E \) is the noise matrix of size \( M \times N \). The signals (from O1, O2 and Oz) are combined to extract the discriminative features. This combination can be achieved by linear transformation of \( X \).

The target at which the user gazes in the SSVEP-based BCI system is determined through a criterion of maxima. More details can be seen at (Friman et al., 2007).

2.2 Canonical Correlation Analyses (CCA)

CCA is a widely technique used 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 \( Y \) consists of simulated stimulus signals. A pair of linear combinations \( x = X^T W_x \) and \( y = Y^T W_y \), called canonical variables, is found by using CCA between the two sets, such that the correlation is maximized. Let \( f_i \) denote the visual stimulus frequency in Hz. Thus, total \( H \) harmonic sine vectors \( s_1, s_2, \ldots, s_H \) and cosine vectors \( c_1, c_2, \ldots, c_H \) for frequency \( f_i \), all of the length \( N \), can be constructed as

\[
s_j = [s_{j,1}s_{j,2}\ldots s_{j,N}]^T
\]

for \( j = 1,2,\ldots,H \), where

\[
s_{j,r} = \sin(2\pi r f_i / f_s)
\]

\[
c_{j,r} = \cos(2\pi r f_i / f_s)
\]

for \( r = 1,2,\ldots,N \), and \( f_s \) is the sampling frequency used for the acquisition of EEG signals. The reference matrix \( Y_i \) of size \( 2H \times N \) corresponding to the stimulus frequency \( f_i \) can be constructed as

\[
Y_i = [s_1^i, c_1^i, s_2^i, c_2^i, \ldots, s_H^i, c_H^i]^T
\]

In our case, we have considered the fundamental frequency and one harmonic as the simulated frequency generator, i.e., \( H = 2 \). CCA method needs to find the weight vectors, \( W_x \) and \( W_y \), that maximize the correlation between \( x \) and \( y \), i.e., it constrains and limits conditions established by Equations 7 and 8.

\[
E[x x^T] = E[x^T x] = E[W_x^T X X^T W_x] = 1 \quad (7)
\]

\[
E[y y^T] = E[x^T y] = E[W_y^T Y Y^T W_y] = 1 \quad (8)
\]

The CCA technique measures the linear association between two sets of variables using its autocorrelation and crosscorrelation (Borga and Knutsson, 2001), i.e., in mathematical terms, the total correlation is calculated as the ratio between the autocorrelation and crosscorrelation of the input and output vectors, as shown in Equation 9.

\[
\rho_k = \frac{E[x^T y]}{\sqrt{E[x^2]E[y^2]}} = \frac{E[W_x^T X X^T W_y]}{\sqrt{E[W_x^T X X^T W_x] E[W_y^T Y Y^T W_y]}} \quad (9)
\]

Finally, the correlation of these signals is performed, and the class obtained through a criterion of maxima.

\[
O = \max_{1 \leq i \leq K} \rho_i, \quad (10)
\]

where \( i \) denotes the number of target and \( K \) the maximum number of visual stimuli.

2.3 Multivariate Synchronization Index (MSI)

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. (Zhang et al., 2014) proposed the use of a S-estimator as index, which is based on the entropy of the normalized eigenvalues of the correlation matrix of multivariate signals. Autocorrelation matrices \( C_{11} \) and \( C_{22} \) for \( X \) and \( Y_i \), respectively, and cross-correlation matrices \( C_{12} \) and \( C_{21} \) 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 $C^i$. The efficiency of our algorithms has been demonstrated in several of our works (Tello et al., 2014a; Tello et al., 2014b). Thus, the following equations are proposed:

$$C_{11} = (1/N)XX^T; C_{22} = (1/N)Y_iY_i^T$$

$$C_{12} = (1/N)XY_i^T; C_{21} = (1/N)Y_iX^T$$

(11)

(12)

A correlation matrix $C^i$ can be constructed as

$$C^i = \begin{bmatrix} C_{11} & C_{12} \\ C_{21} & C_{22} \end{bmatrix}$$

(13)

The internal correlation structure of $X$ and $Y_i$ contained in the matrices $C_{11}$ and $C_{22}$, respectively, is irrelevant for the detection of stimulus frequency (Carmeli et al., 2005). It can be removed by constructing a linear transformation matrix

$$U = \begin{bmatrix} C_{11}^{-1/2} & 0 \\ 0 & C_{22}^{-1/2} \end{bmatrix}$$

(14)

so that $C_{11}^{1/2}C_{11}^{-1/2} = C_{11}$, $C_{22}^{1/2}C_{22}^{-1/2} = C_{22}$ and by applying the transformation $\tilde{C}^i = UC_i U^T$ which results in a transformed correlation matrix of size $P \times P$, where $P = M + 2H$ (Carmeli et al., 2005). The eigenvalues $\lambda_1, \lambda_2, ..., \lambda_P$ of $C^i$, normalized as $\tilde{\lambda}_m = \lambda_m^i/\sum_{m=1}^P \lambda_m^i$ for $m = 1, 2, ..., P$, can be used to evaluate the synchronization index $S_i$ for matrix $Y_i$ as

$$S_i = 1 + \sum_{m=1}^P \frac{\tilde{\lambda}_m^i \log(\tilde{\lambda}_m^i)}{\log(P)}$$

(15)

see (Zhang et al., 2014). Using $S_1, S_2, ..., S_K$ computed for the stimulus frequencies $f_1, f_2, ..., f_K$, the MSI can be estimated as

$$S = \max_{1 \leq i \leq K} S_i$$

(16)

3 Methods

3.1 EEG Acquisition

For the development of the SSVEP-BCI, 12 channels of EEG with the reference at the left ear lobe were recorded at 600 samples/s, with 1 to 100 Hz pass-band. The ground electrode was placed on the forehead. The EEG electrode placements were based on the International 10-20 System. The electrodes used were: P7, P07, P05, P03, P0z, P04, P06, P08, P8, O1, O2 and Oz (see Figure 2(a)). The equipment used for EEG signal recording was BrainNet-36. BrainNet-36 is a device used to record signals Electrocencephalography (EEG) developed by Lynx Technology Ltd. The signals processing was performed by pseudo-online way (simulation) through a sniffer generating a auditory feedback that indicates successful or unsuccessful.

3.2 Visual Stimuli

A coupling structure of four small boxes (4cm x 4cm x 4cm) containing a LED in each one and covered with thin white papers diffuser was mounted in each side of a LCD screen. The volunteers sat on a comfortable chair, in front of a stimulator system, 60 cm far from this. The timing of the four LEDs flickers was precisely controlled by a microcontroller (PIC18F4550, Microchip Technology Inc., USA) with 50/50% on-off duties, and frequencies of 8.0 Hz (left), 11.0 Hz (top), 13.0 Hz (right) and 15.0 Hz (bottom). These frequencies represent commands or classes: Class 1 (11 Hz), Class 2 (13 Hz), Class 3 (8 Hz) and Class 4 (15 Hz), more details are shown in Figure 1.
3.3 Subjects

Three subjects (two males and one female) were recruited to participate in this study (average age: 28.33; SD: 3.21). The research was carried out in compliance with Helsinki declaration, and the experiments were performed according to the rules of the ethics committee of UFES/Brazil, under registration number CEP-048/08. The volunteers were labeled as: s1, s2 and s3. Previous selection of volunteers was performed and topics related to the precaution as visual problems, headaches, family history with epilepsy and problems related to brain damage were taken. All volunteers reported not having any inconvenience for conducting the tests and no one had previous experience in using a BCI.

3.4 Experimental Procedure

During the first ten seconds, the subject onboard the wheelchair can move it forward focusing his/her attention on the stimulus located in top side (11 Hz). After finalizing the first ten seconds, the volunteer fixes his/her attention on the stimulus of the right side (13 Hz) during ten seconds doing the wheelchair turning clockwise (90°). At the end of this time, the volunteer can move the wheelchair forward during other ten seconds and then other ten seconds for turn it counterclockwise in 90° (8 Hz). The trajectory finishes in the last ten seconds, where the wheelchair is moved forward. The time of duration of the experiment was 50 seconds. The stimulus located in the down side (15 Hz) was used only as a panic button or of stop. A explanatory graphic is shown in Figure 2(b).

![Figure 2](image-url)

**Figure 2:** (a) Electrode placement location using 10-20 system for our system.; (b) protocol performed during the tasks.

3.5 Navigation Control

The kinematic model of our unicycle robotic wheelchair is described by a simple non-linear model (see Figure 3) as in eq. 19:

$$\begin{bmatrix}
\dot{x} \\
\dot{y} \\
\dot{\theta}
\end{bmatrix} = \begin{bmatrix}
v \cos \theta \\
v \sin \theta \\
\omega
\end{bmatrix},$$

(17)

where $M = (x,y,\theta)$ is the wheelchair position and orientation in world reference frame, and the pair $(v,\omega)$ is the input control encompassing the linear and angular velocities. In our case, linear $(v = 0.3 \text{ m/s})$ and angular $(w = 9\text{o/s})$ velocities are constant during a variation of time determined $(\Delta t = 1s)$.

- If the wheelchair moves forward: $v = 0.3 \text{ m/s}$ and $w = 0$.
- Moves to right (clockwise): $v = 0$ and $w < 0$.
- Moves to left (counter-clockwise): $v = 0$ and $w > 0$.

From these parameters, if the robotic wheelchair moves forward with a constant velocity of $0.3 \text{ m/s}$ and a time established of $10s$, this will move it forward in $3m$. On the other hand, if the robotic wheelchair turns clockwise with angular velocity of $9\text{o}$ per second and a time established of $10s$, this will have rotated $90\text{o}$.

To calculate the current position of $x$, $y$ and $\theta$ of the robotic wheelchair, it is used the odometry, by calculating the sum of the variations at each instant of time:

$$\begin{bmatrix}
x \\
y \\
\theta
\end{bmatrix} = \begin{bmatrix}
\sum_0^t \dot{x} \cdot \Delta t \\
\sum_0^t \dot{y} \cdot \Delta t \\
\sum_0^t \dot{\theta} \cdot \Delta t
\end{bmatrix} = \begin{bmatrix}
\sum_0^t v \cos \theta \cdot \Delta t \\
\sum_0^t v \sin \theta \cdot \Delta t \\
\sum_0^t \omega \cdot \Delta t
\end{bmatrix}$$

(18)

4 Experimental results

A simulation process was performed with the EEG signals. Initially, signals from the twelve electrodes aforementioned were extracted. In the preprocessing stage, a spatial filter CAR (Common Average Reference) was applied to all channels. Then, the data were segmented and windowed with window lengths (WL) of 1s without overlapping. Then, a temporal elliptical filter between 3-50 Hz was applied. We have used just signals
filtered from O1, O2 and Oz channels as input to the feature extractors to comparison. This is based on the hypothesis that the more high levels of visual evoked potentials are located in these positions. The MEC, CCA and MSI techniques were applied together to the algorithms of control of navigation and the results were compared in terms of performance and trajectory performed (see Figure 1). The comparison of performance was tested for the 3 subjects using WL = 1s as shown in Figures 4, 5 and 6. In addition, these results were also compared with the trajectory and class desired for each feature extractor. A summary of results is shown in Table 1. Information transfer rate (ITR) parameter was calculated according to (Tello et al., 2014a).

<table>
<thead>
<tr>
<th>Acc.[%]</th>
<th>Feature extractor</th>
<th>Duration</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subjects</td>
<td>MEC</td>
<td>CCA</td>
</tr>
<tr>
<td>s1</td>
<td>74.00</td>
<td>88.00</td>
</tr>
<tr>
<td>s2</td>
<td>60.00</td>
<td>80.00</td>
</tr>
<tr>
<td>s3</td>
<td>90.00</td>
<td>68.00</td>
</tr>
<tr>
<td>Mean</td>
<td>74.67</td>
<td>78.67</td>
</tr>
<tr>
<td>± SD</td>
<td>±15.01</td>
<td>±10.07</td>
</tr>
<tr>
<td>ITR</td>
<td>30.92</td>
<td>37.44</td>
</tr>
</tbody>
</table>

5 Conclusion and discussion

According to our results from Table 1, MSI technique achieved the most high values of accuracy with a mean of 88.00 %. Moreover, we can confirm that MSI technique demonstrated to be the most stable due to its low SD (2.00). Due to the fact to obtain high rates of accuracy using MSI, the ITR also resulted high. These ITRs values were calculated based on the mean accuracy of all subjects for each feature extractor evaluated. Our results are considered quite acceptable and still could be improved, taking into consideration that volunteers used for the first time a BCI, and also it is widely known that SSVEP signals in larger time-windows yield better recognition of the visual evoked potentials (Tello et al., 2014a). Thus, the results could be gradually enhanced (a similar path to the desired trajectory) with the increase of WL. Furthermore, our modified version of MSI showed one more time its efficiency even in WL of 1s among the subjects.

Acknowledgement

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References


Figure 4: (a) and (b) showing classified trials and executed trajectory using MEC technique, respectively; (c) and (d) for CCA; and (e) and (f) for MSI in subject 1.

Figure 5: (a) and (b) showing classified trials and executed trajectory using MEC technique, respectively; (c) and (d) for CCA; and (e) and (f) for MSI in subject 2.

Figure 6: (a) and (b) showing classified trials and executed trajectory using MEC technique, respectively; (c) and (d) for CCA; and (e) and (f) for MSI in subject 3.