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Robotic Wheelchair Commanded by SSVEP, Motor Imagery and Word Generation

Teodiano F. Bastos, Sandra M. T. Muller, Alessandro B. Benevides, Mario Sarcinelli-Filho

Abstract— **This work presents a robotic wheelchair that can be commanded by a Brain Computer Interface (BCI) through Steady-State Visual Evoked Potential (SSVEP), Motor Imagery and Word Generation. When using SSVEP, a statistical test is used to extract the evoked response and a decision tree is used to discriminate the stimulus frequency, allowing volunteers to online operate the BCI, with hit rates varying from 60% to 100%, and guide a robotic wheelchair through an indoor environment. When using motor imagery and word generation, three mental task are used: imagination of left or right hand, and imagination of generation of words starting with the same random letter. Linear Discriminant Analysis is used to recognize the mental tasks, and the feature extraction uses Power Spectral Density. The choice of EEG channel and frequency uses the Kullback-Leibler symmetric divergence and a reclassification model is proposed to stabilize the classifier.**

I. INTRODUCTION

The Group of Rehabilitation Robotics of Universidade Federal do Espírito Santo (UFES), Brazil, is developing a robotic wheelchair which can be commanded by eye blinks, eye movements and head movements (Fig. 1). Currently, a BCI is being developed in order to users can command it by brain waves. Although in previous work [1], [2], we have used brain waves to command the robotic wheelchair, in that case the brain waves were dependent of the opening and closing of the user's eye, because the brain waves were dependent of the presence and absence of visual excitation. In this work, the BCI uses only the brain electrical activity (ElectroEncephaloGram - EEG) to identify signal patterns related to the performance of mental tasks.

In this context, several research groups have proposed methods for preprocessing, feature extraction and classification of EEG patterns for BCI usage. Jia et al. [3] perform an offline classification of motor imagery tasks using EEG channels C3 and C4, filtering the signal between 10-12 Hz and using Linear discriminant analysis (LDA) for classification; Liu et al. [4] perform an offline classification of finger movement based on the premovement potential using the EEG channels C3 and C4, and filtering the signal into two distinct frequency bands (0-3 Hz and 9-31 Hz), Common Spatial Subspace Decomposition (CSSD) and Artificial Neural Network (ANN) are used for classification; Anderson et al. [5] perform a pseudo-online classification of three mental tasks using 32 electrodes, the signal is filtered between 8-30 Hz, Short-Time Principal Component Analysis (STPCA) is used for feature extraction and LDA for classification; Blankertz et al. [6] perform an online classification of premovement potentials with user feedback using 128 electrodes, Common Spatial Pattern (CSP) and LDA.

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Teodiano F. Bastos, Sandra M. T. Muller, Alessandro Benevides and Mario Sarcinelli-Filho are with Departamento de Engenharia Elétrica, Universidade Federal do Espírito Santo (UFES), Vitoria, 29075-910 Brazil (+5527 40092077; fax: +5527 40092644; e-mail: teodiano@ele.ufes.br).

Fig. 1. Robotic wheelchair developed in UFES/Brazil.

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When using the paradigm of Steady-State Visual Evoked Potential (SSVEP), the fundamental component and harmonics of a flickering frequency of a visual stimulus are present in the ElectroEncephaloGram (EEG) signal. The BCIs based on these potentials are called SSVEP-BCI, and the interest in developing this kind of BCI is mainly due to the robustness of this phenomenon, since this potential is an inherent response of the human brain. This leads to a fast adaptation of the individual to operate such BCI [7].

As SSVEP-BCIs support a greater number of commands than the BCIs based on motor imagery [8], they could achieve higher Information Transfer Rate (ITR). For instance, BCIs that are not based on the SSVEPs reach ITR from 10 to 25 bits/min, while the current SSVEP-BCIs reach up to 100 bits/min [9]. The high ITR in a SSVEP-BCI is due to the high number of commands (up to 13 simultaneous commands [10], [11]), and because the SSVEPs are induced by external visual stimuli which are more robust and easier to control than internally generated stimuli. Thus, according to [12], the advantages of this kind of BCI are the high ITR with minimum training requirement, robustness against noise and artifacts and the relative easiness to increase the number of commands. However, the stimulation with small squares flashing can cause fatigue if the BCI is used for a long time. Also, a SSVEP-BCI depends on some muscle control, which leads to an inefficiency for some patients with severe motor dysfunction, despite some suggestions for SSVEP controlled by the user attention, which would be defined as an independent BCI [13], [14].

In this work, SSVEP, motor imagery and word generation will be used in a BCI to command a robotic wheelchair.

II. SYSTEM DEVELOPED

For the research with motor imagery and word generation, the EEG data were provided by IDIAP Research Institute [15]. This data set contains EEG signals from three normal subjects during four sessions, without feedback. In each session the subject performed randomly three mental tasks, which are the imagination of right or left hand movements and generation of words beginning with the same random letter. EEG signals were recorded at 512 Hz with a Biosemi system using a cap with 32 integrated electrodes located at the standard positions of the International 10-20 system. No artifact rejection or correction was employed.

An analysis of the Linear Auto-correlation Function and nonlinear Auto-correlation Function were performed to determine if the signal is sub-sampled or over-sampled. Both functions were calculated for the EEG signals of all electrodes and, as a result, the signal was sub-sampled to 64 Hz. Small time windows of EEG signals, with a fixed number of samples, were taken to simulate real-time classification. The time windows are continuously displaced by a sample (the sliding window technique). Thus, after the first time window is filled, each following window is generated by displacing the current window by one sample, and the BCI classification rate is equal to the sampling rate signal. The size of the time window should be enough to contain most of the influence of a sample in the next sample and characterize a pattern that can be recognized by the classifier. To estimate the size of the time windows, the coefficients of the Partial Auto-Correlation Function were calculated for the EEG signals and a time window size of about 1 second was obtained [16].

For each time window, the Power Spectral Density (PSD) of the EEG signal is calculated. PSD is the Fourier transform of the Auto-Correlation Function (ACF) of the signal, if it can be considered Wide-Sense Stationary. PSD describes how the signal power is distributed in relation to the frequency (power can be defined as the squared signal value). As the EEG signal was sub-sampled to 64 Hz, the PSD was designed to return one coefficient for each integer value of frequency, resulting in 33 coefficients.

A method to smooth the classifications was developed [17]. Classification windows were taken to behave as time windows and perform a data reclassification. These windows are composed of previous classifications and are continuously displaced by one classification, resulting in a reclassification with the same sampling rate of the signal (Fig. 2).

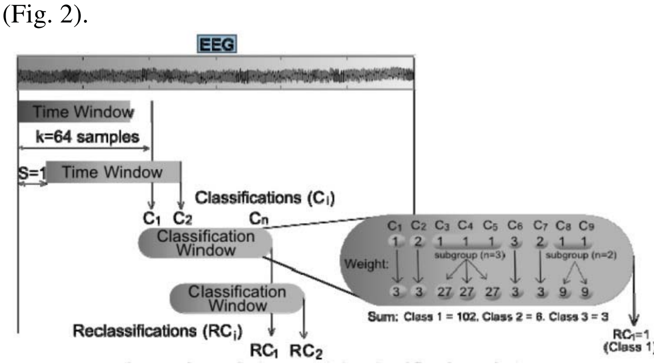

Fig. 2. Time windows and the classification windows.

The new classifier output will be the class with a higher weight in this classification window. The weight of each previous classification is given in relation to the size of the subgroup of equal classes that it belongs in the classification window. The weight is calculated by the inverse of the probability of a repeated occurrence of a class.

Using this method, the classifier was able to identify the three classes and to obtain results above random (33%) success rate.

In the other research carried out, now using SSVEP, the trials were developed with the volunteers sat on a comfortable chair, in front of a 17-in LCD display, 0.7 m far from it. They were asked to watch a stimulation screen generated by an FPGA based subsystem. Such stimulation screen consists of four stripes presented simultaneously to the user plus of four LEDs used as a visual feedback, as illustrated in Fig. 3. Twelve EEG channels, with the reference electrode at the left ear lobe, sampled at 600 samples/s and filtered with a 0.1 to 100 Hz bandpass, were recorded. The equipment of EEG signal recording used is a BrainNet-36, from EMSA Equipamentos Ltd.. The signal is acquired in intervals of 1 s using a proxy system, developed in this work, called EEGProxy. Using the extended international 10-20 system, the locations for the electrodes are P7, PO7, PO5, PO3, POz, PO4, PO6, PO8, P8, O1, O2, and Oz. At the preprocessing step, digital low-pass filtering was performed using a 5th-order elliptic filter, with a bandpass from 3 to 60 Hz. Also, a spatial filter based on the Common Average Reference (CAR) method was implemented.

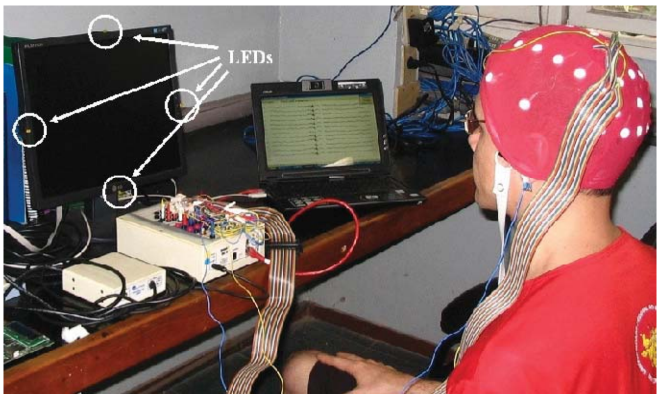

Fig. 3. Acquisition system with visual feedback (biofeedback).

In the first trial, a volunteer was asked to watch the screen without stimulus, which is called rest state. After a rest state acquisition of two minutes, only one trial of 160 s was carried out by the volunteer. In this trial the subject was asked to watch each strip for 10 s four times. The flickering frequencies were 5.6 rps (top), 6.4 rps (right), 6.9 rps (bottom) and 8.0 rps (left). A voice alarm was used to warn the volunteer to change the strip observed.

The trial was carried out without using the biofeedback system and four healthy male volunteers, aged between 23 and 36, named as Vol15, Vol21, Vol25 and Vol28, participated in this trial. The second trial was performed using the visual feedback and only three volunteers Vol1, Vol10 and Vol28 participated. Again the EEG signal during the rest state was acquired and after that the user was free to choose the stripe to be gazed.

The inputs for the classification step are results from a F-test, used to feature extraction [18]. The input parameters of the classifier are related to peaks that overshoot the SFTcrit value. There is no metric for the points which are desired to classify and therefore the classifier chosen is a rule based one. For that, a decision tree (Fig. 4) was developed and its parameters were related to the amplitude of these peaks and the associated frequency value. These parameters are converted to attributes capable of modeling the system suitably.

For each sample, the decision tree developed has three attributes, A1, A2 and A3, concerning to the first ten peaks. More details can be checked in [19]. There is one class for each stimulus frequency, and when the decision tree classifies the sample as belonging to the class X it means that sample was not classified. The training step is unnecessary in this application, because the classifier use is straightforward [20]. This represents a great advantage for decreasing the computational cost.

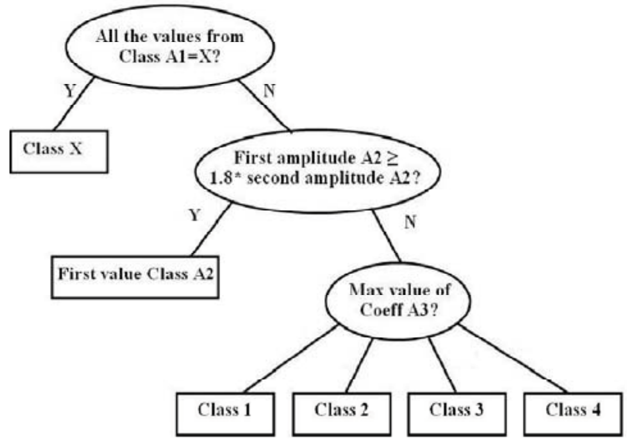

Fig. 4. Decision tree implemented for the SSVEP-BCI developed.

III. ROBOTIC WHEELCHAIR

After the research carried out with brain signals, the SSVEP-BCI system was implemented onboard the robotic wheelchair, using a compact and low-power computer (a mini-ITX EPIA computer with 1 GHz of clock frequency and 1 GB of RAM). In the BCI developed, such computer has the function of processing the EEG signal recorded and classify them to generate the command to the wheelchair. It is located in the back part of the wheelchair, as well as the FPGA responsible for the stimulus generation, as illustrated in Fig. 5.

A volunteer was able to guide the robotic wheelchair through the lab (Fig. 6). The stripes were used to command the movements of the wheelchair forward (the strip in the top), left (the left strip), right (the right strip) and stop it (the strip in the bottom).

IV. CONCLUSIONS

This work presented a robotic wheelchair that can be commanded by a BCI through SSVEP, Motor Imagery and Word Generation. For these two latter techniques, the application of the proposed methods resulted in a classifier able to identify the three classes and to obtain results above random (33%) success rate. In addition to that, the stability of the classifier signal and the ITR make possible its application in a BCI to command a robotic wheelchair, in the same way of using SSVEP-BCI, in real time.

When using SSVEP, the development is split in some steps that are important to the efficient operation of the BCI. Since the protocol of the EEG signal acquisition up to the processing step, it is important to keep in mind that, in future works, all these steps have to be simplified to obtain good performance. Also, a better graphical interface is important to interact with the user.

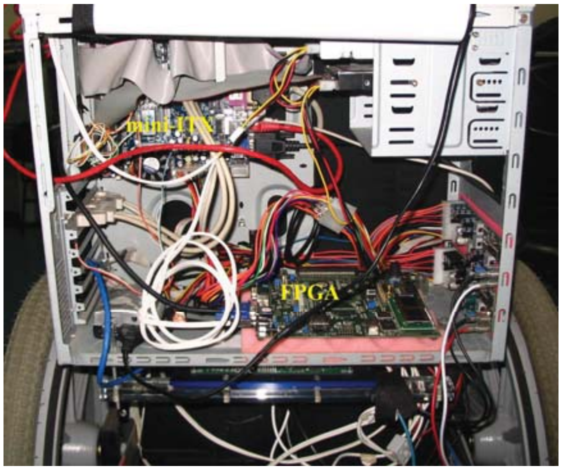

Fig. 5. The mini-ITX and the FPGA used in the BCI system.


Fig. 6. Using the SSVEP-BCI to command a robotic wheelchair.

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