IEETA BRAIN COMPUTER INTERFACE
Towards a Rapid Prototyping and Multi-Application System

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Abstract: Recent advances in computer hardware and signal processing assert that controlling certain functions by thoughts may represent a landmark in the way we interact with many output devices. This paper exploits the possibility of achieving a communication channel between the brain and a mobile robot through the modulation of the electroencephalogram (EEG) signal during motor imagery tasks. A major concern was directed towards designing a generalized and multi-purpose framework that supports rapid prototyping of various experimental strategies and operating modes. Preliminary results of brain-state estimation using EEG signals recorded during a self-paced left/right hand movement task are also presented. The user successfully learned to operate the system and how to better perform the motor-related tasks based on outcomes produced by its mental focus.

1 INTRODUCTION

In recent years, the appealing idea of a direct interface between the human brain and an artificial system – called *Brain Computer Interface* (BCI) – has motivated a growing community of researchers (McFarland, 2006). The conceptual approach is to model the brain activity variations and map them into some kind of actuation or command over a target output (*e.g.*, a computer interface or a robotic system). Continuing advances in a number of fields have supported the thesis that the concept is viable, although a significant research and development effort has to be conducted before these technologies enter routine use. Nowadays, the principal reason for the BCI research is the potential benefits to those with severe motor disabilities (*e.g.*, amyotrophic lateral sclerosis, brainstem stroke or severe cerebral palsy) (Kubler et al., 2005).

The combination of these reasons led the authors to gradually start a project aiming to initiate a long-term multidisciplinary research by combining developments in relevant fields, such as cognitive neuroscience, brain imaging, pattern recognition, electronics and computing. The ultimate goal is to promote the involvement of under and post-graduate students in international level stages such as competitions of the grade of BCI2000 (Schalk et al., 2004) and similar. In the middle-term, the main scope has been the design and development of a BCI system to exploit the benefits of a closer interplay between neurosciences and robotics. A hypothesis is that brain-actuated control of a robotic device will improve human-robot interfaces and facilitates robot programming.

Bearing this in mind, this paper presents the first steps towards the development of an EEG-based BCI system that analyzes the brain activity of a subject, tries to find out its intentions and generates output commands controlling an appropriate output device. The relevant feature of this implementation includes the movement imagery, based on the mu rhythms, as control strategy to command a Khepera mobile robot (Pineda et al., 2000). A major concern was directed towards designing a generalized framework that supports rapid prototyping of various experimental strategies and operating modes. From the current stage of development, based on Matlab and Simulink, it stands out the high versatility of implementation that allows the comparison of different spatial filters, spectral analysis algorithms and signal processing methods. Although some issues are yet to be addressed, our BCI is already mature for practical experiments and to obtain the first conclusions on the potential of the proposed solutions.

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The remainder of the paper is organised as follows. Section 2 reports previous studies that produced valuable insights, focusing on strategies employed and the potential of mu rhythms in actual BCIs. Section 3 describes the design options, the developed tools and the applications of the IEETA BCI. Section 4 presents preliminary results of brain-state estimation using EEG signals recorded during a self-paced left/right hand movement tasks, while controlling the Khepera mobile robot. Section 5 concludes the paper and outlines the perspectives of future research.

2 RELATED WORK

Over the past decade, several working BCI systems have been described in the literature (Jos et al., 2004, Pfurtscheller et al., 2006, Wolpaw et al., 2003). These systems use a variety of signal acquisition methods, experimental paradigms, pattern recognition approaches and output interfaces, requiring different types of cognitive activity. Most solutions rely on brain electrical activity measured through electroencephalogram (EEG). Despite their poor spatial resolution, this non-invasive technique has proven to be a useful and practical tool in experimental research, mainly due to fast recording, easy subject preparation and reduced equipment required. Furthermore, the relationship between EEGs and brain function is well documented in the literature.

One type of BCI that has been extensively studied derives information either from the user's movements or the imagination of movement. These movement-based BCIs recognize changes in the human mu rhythm, which is an EEG oscillation recorded in the 8-13 Hz range from the central region of the scalp overlying the sensoriomotor cortex (Kuhlman, 1978, Pfurtscheller and Lopes da Silva, 1999). This activity is most pronounced when subjects are at rest, but not planning to initiate voluntary movement. At least a second before subjects initiate voluntary movement, the mu rhythm over the hemisphere contralateral to the region moved shows a decrease in amplitude and thus power. This attenuation becomes more symmetric over both hemispheres as subjects actually initiate the movement and remains until shortly after the movement is initiated. Mu activity returns to baseline levels within a second after movement is initiated and may briefly increase above baseline (Fatourechi et al., 2007, Pineda et al., 2000). These activity dependent changes in mu activity have also been called Event Related Desynchronization (ERD) and Event Related Synchronization (ERS) by Pfurtscheller and his co-workers (Pfurtscheller and Lopes da Silva, 1999).

The mu rhythm thus has potential for BCIs for many reasons. It is present in nearly all adults, including many individuals with motor disabilities. Since it's easy to train in subjects while they are awake with eyes open (Kuhlman, 1978, Pfurtscheller and Lopes da Silva, 1999) and can be affected by visual and imagined input (Muthukumaraswamy et al., 2004, Pineda, 2005, Hoshi and Tanji, 2006), it may be possible for users to learn to use a mu rhythm based BCI system by means of a multiplicity of stimuli and cognitive strategies. Therefore, the pattern recognition may be simple: detecting power changes can be fruitful in BCI design. Finally, the mu rhythm can be modulated in either or both hemispheres (Pfurtscheller and Lopes da Silva, 1999, Pineda et al., 2000).

These observations led us to utilise motor imagery as control strategy to achieve asymmetrical electrocortical responses and to use left-right differences in the sensoriomotor EEG to provide the required control options of a two dimensional environment.

3 IEETA BCI: DESIGN AND OPERATION

The IEETA BCI system was conceived having in mind the application to which it will be applied: control of a robotic device. Moreover, the BCI tools are optimized for each individual user by providing him with a training period in the presence of feedback. Indeed, present BCI systems depend on user control of brain electric activity, such as amplitude in a specific frequency band (*e.g.,* mu rhythms) in EEG recorded over a specific cortical area (*e.g.,* sensoriomotor cortex).

This section describes the relevant development steps since they will reveal much about the problems, challenges and tradeoffs of the complete BCI prototype, as well as guide the selection of alternative designs.

Matlab® and Simulink® were the platform chosen to develop the BCI system. This choice is justified by the fact that it's the widely tool used in signal processing and classification. These two areas represent the main base of any BCI system.

Due to the flexibility of Matlab programming, all the algorithms are written in Matlab code whereas the driver of the acquisition hardware was created employing C++, using a wrapper to integrate it.

Another important aspect of developing any system in Matlab® is that, this can be done in a high abstraction level, letting the developer focus on the problems of the system and not on the tools that support it. Each new module can be chosen from Simulink library. Simulink library provides many Signal Processing modules for direct implementation. When a new module is needed with a specific task, it can be implemented using an S-Function.

S-Functions uses a callback method to perform each task that operate flawlessly within the main system, this way we guarantee a temporal performance, essential in online analysis.

3.1 EEG Recording

EEG signals were recorded from eight scalp electrodes placed over central (C3, C4), frontal (F3, F4) and parietal (P7, P8, P3 and P4) locations according to the 10-20 international system and referred to a linked-ear reference (Jasper, 1952). Using this spatial location we assume that a generic motor imagery task can relate to different subsets of cortical areas activation, resulting in the excitability of different regions such as the Premotor Cortex, the supplementary motor area, the primary motor cortex and the sensoriomotor cortex (Porro et al., 1996, Lacourse et al., 2005, Lotze et al., 1999).

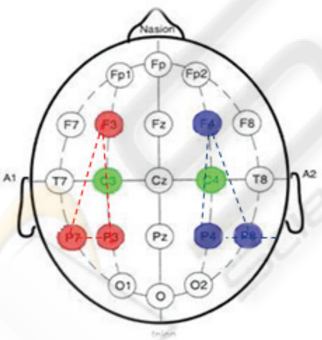

Figure 1: Spatial Location of the EEG electrodes over the frontal, central and parietal areas.

The BCI user utilizes a portable EEG acquisition system (Figure 2) with a sampling rate of 256 Hz. This EEG system imposes a maximum number of 8 acquisition electrodes. This difficulty becomes secondary by the advantage of using a portable system that represents minor power consumption, essential to the implementation of a future ambulatory system. Another advantage resulting from using a small number of electrodes is the smooth online performance of the BCI system, as trivial to assume that a higher number of EEG electrodes results in a higher number of signals to process that if not equipped with fast, and expensive, hardware system could inflict slowdowns in the real-time processing.

Figure 2: TrackIt system: ambulatory acquisition of EEG signals (from *LifeLines Ltd*).

3.2 Control Paradigm

According to (Arroyo et al., 1993) mu waves are almost constantly present when the subject is relaxed and are heavily suppressed when the subject performs a motor (imagery or real) task exciting the contralateral side, i.e. mu waves disappear over the left brain hemisphere when the right hand is moved and vice versa. In addition, humans can learn to modify the amplitude of the mu rhythm after prolonged training (on the order of weeks or months) with the help of mental activities alone. This is the starting point of the systems described in (Fabiani et al., 2004, Guger et al., 2001, Wolpaw et al., 2000). Their idea is to take that amplitude – measured only by one pair of electrodes – and translate it into (one-dimensional) cursor movement. Using a simple computation, it estimates the FFT of the ongoing EEG (“online”), taking the square root of the power associated with the mu rhythm frequency range, and comparing the resulting value with adaptable voltage ranges. This leads to a trivial quantification (or *classification*) encoding the mu rhythm amplitude, and is directly translated into the movement of a cursor on a feedback video screen, where low amplitudes move the cursor down, while high amplitudes move it up (the magnitude of the upward or downward movement being part of the quantification, too).

Although the accuracy that can be achieved with this system is relatively high (in up to 95% of all cases, the system really does what the user wants it to do), it cannot serve as the basis for a practical device, since it is very slow. To cope with this problem, the solution relies in the multi-dimensional control provided by distinct EEG features. The idea was to record the EEG at two different sites on the scalp, hoping that subjects would be able to learn to intentionally vary the two mu rhythm amplitudes simultaneously and independently. The projected system was much more practicable, since it possessed the potential to "emulate" a computer mouse to a certain extent. However, despite the correctness of the "independence hypothesis", the outcome was not much more than a laboratory phenomenon, because the achieved accuracy did not exceed 70%. Kostov and Polak, (2000) have also shown that subjects can move a virtual object up and down on a computer screen by issuing various mental activities during a time window delimited by the pressing of two manual switches.

3.3 Signal Processing and Classifier

Each EEG raw signal was filtered in the 8-13 Hz band by a *20*-order Band-Pass Butterworth Filter. After filtering, the signal was segmented in customized blocks of 128 samples (0.5s). Each signal block was transformed by a surface Laplacian in F3, C3, P3 and P7 for the left Hemisphere and F4, C4, P4 and P8 for the Right Hemisphere (see Figure 1).

The power spectrum Estimation was performed using the Yule-Walker Method (Kay, 1998). Each vector (8 channels with 128 frequency components) is then analysed by the ERD (*Event Related Desynchronization*) block, which verify for a specific frequency band if the ERD is confirmed. There are two ERD modules, one for each hemispheric signal.

The Classifier (Figure 3) has two inputs, one for each ERD block. It was implemented by mean of a decision tree, so if only the Right Hemisphere signal verifies the ERD, the classifier output is "LEFT". If only the Left Hemisphere signal verifies the ERD, then the classifier output is "RIGHT". If both the signals verify the ERD then the output is "FORWARD". If neither one of the signals verifies the ERD, then the output is "STOP". In this way, with only 2 mental tasks, we obtain 4 possible control orders.

The majority of the BCI systems implemented devote a great part of the system resources and development time in the classifier. Nonetheless, a very important part of any BCI system, the authors of this BCI system realize that the importance of the classifier can easily be minored if we get better and enhanced features from the mental tasks carried out.

This can be achieved selecting the best electrodes set-up, signal processing methods and new EEG processing techniques such as ERD, ERS, P300 and others yet to be found.

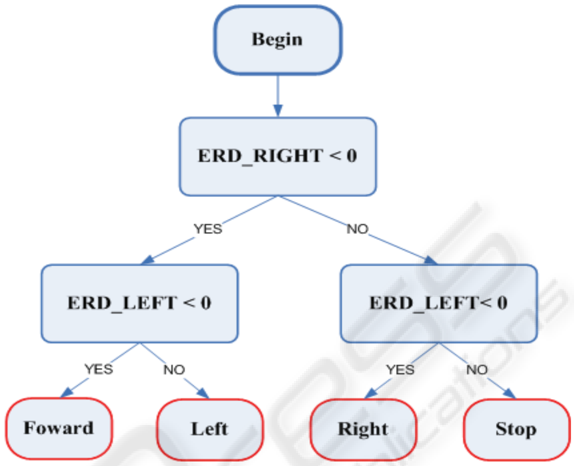

Figure 3: Binary Tree Classifier perceiving four possible states based on the two ERD features.

3.4 BCI Output

The mobile robot used as the control application was a small Khepera. The Khepera robot (5.7 cm diameter), is a two-wheeled vehicle with 8 infrared sensors representing the ideal analogy for a wheelchair.

Two other graphical applications where developed, BioFeedback I and BioFeedback II, both mainly used in user training.

BioFeedback I provides the feedback in a graphical way, displaying one of four images according to the classifier output - "RIGHT", "LEFT", "FORWARD", "STOP".

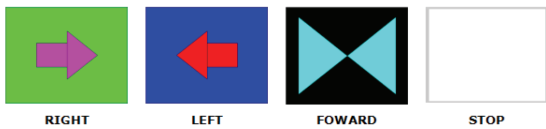

Figure 4: Training Module where each image correlates with a classification output (BioFeedback I).

Feedback is provided by means of coloured arrows, one for each mental task, for easily recognition of the system output.

The other graphical application (BioFeedback II) is also used in the online test of the system, and it's a classical application of the BCI systems. The goal of this application is to place the cursor on one of three possible areas (Figure 5). The cursor is controlled by means of the classifier outputs – “RIGTH”, “LEFT” and “FORWARD”.

Figure 5: Second Graphical Application proposed for user training (Biofeedback II).

The final application is the control application depicted before. This output module, depending on what the classifier output is, controls the velocity on each wheel. The Khepera robot provides 8 infrared sensors, this enables, in integration with the system, to detect when the robot reaches a wall, allowing in this case only two possible movements – forward and the opposite wall direction movement.

The control communication with the Khepera Robot is performed through RS232 protocol and using the communication toolbox available from Matlab® in real-time performance.

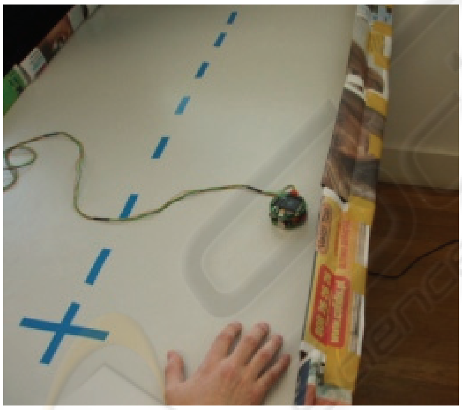

Figure 6: Control output.

4 EXPERIMENTAL RESULTS

4.1 Users' Protocol

During a session, the subject sat in front of a screen, and was asked to remain still (Figure 7a). Scalp electrodes (see montage in Figure 1) acquired 8 EEG channels, each one of them referenced to an electrode in the right ear lobe.

The Experimental Procedure was designed in 3 steps. First we acquire the Baselines through the BCI_GetBase sub-system that is essentially the BCI system without the output module, sharing all the main modules and its configuration.

The Baseline is the core of any ERD based system. We acquire 3 Baselines, for 3 mental tasks: imagery finger tapping; imagery open/close hand; imagery free hand movement. We choose three different baselines, due to the fact that the definition of baseline is related with the definition of No Control (NC) state, that is when there is no intentional control, e.g., during periods of thinking or monitoring that do not correspond to the cortical excitation achieved by the two motor imagery tasks that are asked to the user. NC control support is necessary for most types of machine or device interactions where frequent actions are spaced by periods of inaction. In this way, and using the contralateral propriety of cortical activation, the baseline that shares all the common underlying brain activity of the motor imagery tasks asked to the user, is its opposite task, e.g., if we are analysing the presence of a right motor imagery task we compare the EEG signal with the recorded baseline for the left motor imagery task performed before, detecting in this way all the difference in signal amplitudes related to the modulation of the mu rhythms.

After the record of the baselines the subject was given three possible conditions to control the Khepera robot.

1) Rest: the subject, sat in a comfortable chair, was asked to relax as much as possible and think of nothing in particular.

2) Self-generated movements: subject is asked to move each finger;

(3) Imagination: subjects were instructed to image performing the self-generated movement without actually doing it.

Only the results achieved using the motor imagery tasks were explored in validating the preliminary system results.

4.2 Data Analysis

The degree of mu suppression occurring during the imagery of movement can be expressed as a relation with the peak power value at rest and typically shows an average decrease that depends on the level and “quality” of attention.

After we got all the 3 Baselines for each ipsilateral hemisphere (Figure 8 and 9), the system automatically chooses what is the Baseline that offers the best results. The notion of a good Baseline

Figure 7: Experimental Environment.

is associated with the absence of involuntary desynchronization or artefacts.

With the baselines for each mental task, the next step is to train the user in the system. To promote a fast learning on how to better control the cerebral rhythms it's proposed to the user the BioFeedback I and II usage for a typical period of 30 minutes that can be (desirably) increased depending on the user available time

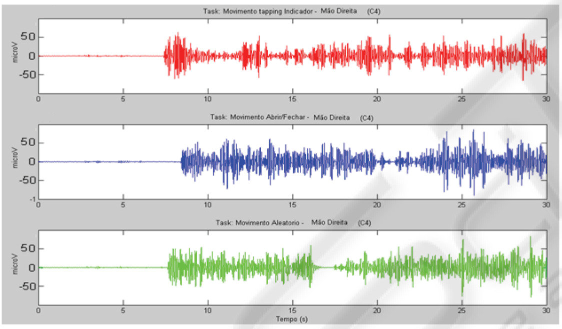

Figure 8: Baselines for: imagery finger tapping, imagery close/open Hand and imagery free hand movement respectively (Ipsilateral Movement - Right Hand, Right Hemisphere).

Finally, after the acquisition of the Baseline and the (ideal) extensive training of the user, we analyse the user performance in controlling the Khepera Robot. In this step, all the BCI system configuration is set up specifically for the user, this is easily achieved due to the rapid-prototyping characteristic we included in the system.

These distinctive features of any BCI system relate to the importance of the user training that after a few hours of train could certainly boost the system performance.

The control of the Khepera robot was done in a free environment. The user had to move it to two possible areas as shown on Figure 7b using the motor imagery tasks depicted before.

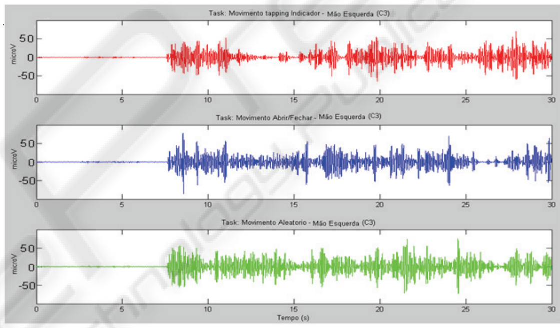

Figure 9: Baselines for: imagery finger tapping, imagery close/open Hand and imagery free hand movement respectively (Ipsilateral Movement - Left Hand, Left Hemisphere).

Examples of the ERD achieved for both the "Right" and "Left" areas in the contralateral spatial filtered electrodes (C3 and C4) are shown below.

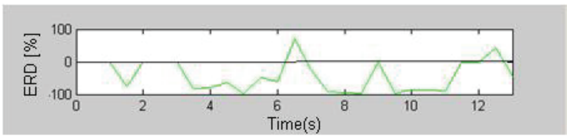

Figure 10: ERD for the spatial filtered signal at C3 (Right Area target).

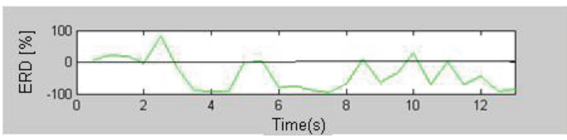

Figure 11: ERD for the spatial filtered signal at C4 (Left Area target).

The user achieved a 70% correct classification rate for each direction in a total of 7 trials. The classification rate has evolved during the sequential trials. Through time, the user developed own ways to better control the robot. This fact implies that an extensive training is essential to obtain very good results.

Nonetheless the lack of extent of the online results, as referred earlier, these results are preliminary and mainly used to validate the system as a promising BCI structure.

5 CONCLUSIONS

We have shown the development of a multi-application BCI system from the source to the output. Using rapid-prototyping tools we ensured an efficient time-progress window of development. This also represents a proficient ability to perform several optimizations quickly and in highly integration with the structural hierarchy of the BCI system implemented.

An important aspect about this BCI system is its modular structure that allows it to perform a different function just by creating a new output module. This modular structure also improves the time-progress window due to its parallel development and optimization suited for each module individually.

This system represents a new BCI platform developed using efficient and widely used signal processing tools ensuring in this way a maximum focus on the project itself and not on the development tools that support it.

In spite of being in an inborn stage this system provided encouraging results in the preliminary online test made. The user demonstrated satisfaction in using the system and confirmed its controllability.

More and extended online tests are needed to perform increasable optimizations, nonetheless, this process is already on course in two different BCI areas (Control and Bio-Encryption), that due to the system modularity interchange results and possible optimization between them in order to achieve the best possible results.

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