Interface Cérebro-Computador (BCI) no Paradigma de Imagiologia Motora

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Abstract

Brain-Computer Interfacing is a very active research field at the moment, attempting to create a direct channel of communication between the brain and a computer. This is especially important for patients that are "locked in", as they have limited motor function and thus require an alternative means of communication. One way of controlling a Brain-Computer Interface (BCI) is through the imagination of motor tasks, which produce measurable changes on the ongoing Electroencephalogram (EEG), such as the so called Event-Related Desynchronization (ERD). Traditionally, ERD is measured through the estimation of EEG signal power in specific frequency bands. In this thesis, a new method based on the phase information from the EEG channels, through the Phase-Locking Factor (PLF), is proposed. Both feature types were tested in real data obtained from 6 voluntary subjects, who performed 7 motor tasks in an EEG session. The features were classified using Support Vector Machine (SVM) classifiers organized in a hierarchical structure. The results show that the PLF features are better, with an average accuracy of $\approx 86\%$, against an accuracy of $\approx 70\%$ for the band power features. Although more research is still needed, the PLF measure shows promising results for use in a BCI system.

Keywords: Brain-Computer Interface, Imagined Motor Tasks, Electroencephalogram, Event-Related Desynchronization, Band Power Features, Phase-Locking Factor, Support Vector Machine.

1 Introduction

Computers are an ubiquitous and useful technology, providing an easy and improved means of communication. Unfortunately, some users, suffering from severe motor disabilities such as Amyotrophic Lateral Sclerosis (ALS) lack the ability to operate a computer, although their cognitive capabilities are essentially intact. So why not go directly to the source of all thought and action: the brain? Can we extract enough information from the brain to create a new channel of communication between humans and machines? These and other questions are the main focus of current research in Brain-Computer Interfaces (BCIs), a method through which measurements of brain activity are translated into commands for a computer or other devices [1].

The main goal of this work is to develop a BCI system based on the imagination of motor tasks. To do so, the appropriate physiological properties are investigated, namely Event-Related Desynchronization (ERD) and Event-Related Synchronization (ERS), and two approaches are used to identify them in the Electroencephalogram (EEG). While the first approach uses the signals' power is specific frequency bands, the second uses the concept of Phase-Locking Factor (PLF), a measure of synchronization between two signals.

2 BCI Definition and Structure

A BCI is defined as a system that measures and analyses brain signals and converts them in real time into outputs that do not depend on the normal output pathways of peripheral nerves and muscles [2]. It can be inferred from this definition that in order to have successful BCI operation, a closed loop of information is necessary between two adaptive controllers: the user, who produces specific brain signals that encode intent, and the BCI, which translates these signals into outputs that accomplish the user's intent, providing feedback to the user [3].

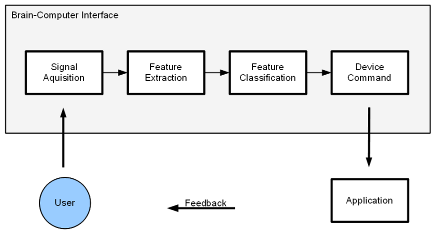

Figure 1: Basic BCI structure.

Regardless of its purpose or recording methods, a BCI consists of four essential elements [3], depicted in Figure 1:

- Signal Acquisition

  The first step in BCI operation is the acquisition of brain signals. Electrophysiological systems measure the electrical activity of brain cells with electrodes either placed on the scalp (EEG), on the cortical surface (ECoG) or with intracortical devices. Of these methods, the most widely used for BCI operation is the EEG, as it is a noninvasive, cost effective and simple technique, with good temporal resolution [3].

- Feature Extraction

  This step transforms the raw brain signals into useful information to control the BCI, which depends on the type of mental task that the BCI is based on. Time domain feature extraction methods include filtering, wavelet transform and parametric models such as Auto-Regressive (AR) models. Frequency domain methods mainly rely on band power estimation using Welch's Method, Morlet Wavelets and AR models.

- Feature Classification

  Once the features have been obtained from the EEG, it is necessary to classify them according to the experiment (paradigm) characteristics. Most classification techniques rely on Machine Learning algorithms like Neural Network (NN), Hidden Markov Model (HMM), Threshold Detectors, Fisher's Discriminant Analysis (FDA), Support Vector Machine (SVM) and Linear Discriminant Analysis (LDA) [4].

- Device Output

  This stage encompasses the transformation of the previously identified brain activity into outputs that accomplish the user's intent. According to [3], there are two types of BCI applications: 1) direct control of assistive technologies and 2) neurorehabilitation.

3 Neurophysiology of Motor Tasks

In order to operate a BCI users have to acquire conscious control over their brain activity [1]. One way of doing so is by concentrating on a specific mental task, such as a motor task. It has been shown that the imagination of movements (i.e. simulating movements in the mind without actually performing them) originates similar EEG patterns as actual movement [5]. The Primary Motor Cortex (PMC) is the area of the brain responsible for planning and executing movements. The most characteristic brain oscillation (visible in the EEG) arising from this area is the μ rhythm (8 - 12 Hz). This rhythm is modulated by the tasks of preparation, observation or imagination of movement, which induce time-locked changes in the activity of neuronal populations. Note that instead of one uniform rhythm, the sensorimotor area generates a variety of rhythms that have specific functional and topographic properties [5]. As such, a certain motor task represents frequency specific changes of the ongoing EEG, which can either be an increase in power (termed Event-Related Synchronization (ERS)) or a decrease in power (Event-Related Desynchronization (ERD)).

ERD and ERS reflect the changing dynamics between main neurons and interneurons that control the frequency components of the ongoing EEG [6]. While ERD is correlated with activated cortical areas, ERS α band rhythms during mental inactivity introduce inhibitory effects. Note that the PMC has a very specific organization with each part of the body clearly mapped to a region of the PMC, as can be seen in Figure 2.

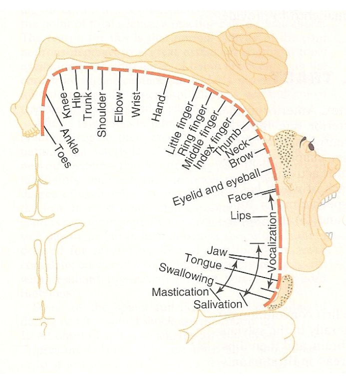

Figure 2: Degree of representation of the different muscles of the body in the motor cortex [7].

Put shortly, a certain motor task induces ERD over the corresponding cortical area while there is ERS in unrelated areas. This implies that the resting (inactive) state of the motor cortex corresponds to a widespread and highly synchronized rhythm, which, during a motor task, loses synchrony over the task specific region. Thus, it is expected that EEG channels corresponding to the task's cortical area lose coherence from the other channels. From this, it can be understood that ERD/ERS is the fundamental physiological property to be detected in a motor imagination BCI system.

4 Methods

4.1 Experimental Setup

The acquired signals consist of EEG data from 6 subjects (2 female, 4 male, ages (22.3 ± 0.5) years, all right handed). The subjects, fitted with a 64-electrodes cap (10-20 system) connected to a Brain Products' QuickAmp amplifier, were comfortably sitting in a chair in front of a CRT computer screen which conducted them throughout the experiment. The cue-based BCI paradigm consisted of seven different motor tasks: no movement (CC), movement of the feet (left and right – LF, RF), movement of the legs (left and right – LL, RL) and movement of the hands (left and right – LH, RH).

One session was recorded for each subject. The sessions comprised two runs, separated by a short break. Each run consisted of two groups of trials, being the first group dedicated to actual realization of the above motor tasks, while in the second group users were asked to imagine the motor tasks. Each group comprised three cycles through the motor tasks. Each trial started with the presentation of a fixation cross over a blank screen. After 1 s a figure appeared indicating the motor task to be executed, lasting for 4 s. At the end of this period both the fixation cross and figure are replaced with a relaxation indication, giving the subjects the opportunity to blink, lasting for 2 s. A final blank screen (1 s) allowed the transition to the next trial. See Figure 3 for a graphical representation of the trial structure.

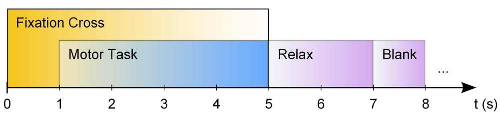

Figure 3: Structure of a trial of the EEG recording sessions.

4.2 Signal Preprocessing

The raw EEG signals were downsampled from the original 2000 Hz to 500 Hz and then band-pass filtered between 5 Hz and 45 Hz. Subsequently, the trials were isolated and ordered. From the original set of electrodes a subset of 14 channels was selected over the Primary Motor Cortex. For this subset a small Laplacian filter was applied to each channel taking into account its four nearest neighbors. No artifacts were removed.

4.3 Band Power Features

The classic method to identify and measure ERD/ERS is by computing the power of the in-put signals in specific frequency bands. To do so there are several different techniques currently used in the development of BCI systems, such as the method employed by Pfurtscheller and Lopes da Silva in [6] (by bandpass filtering and squaring the amplitude samples of the EEG), using the Fourier Transform [4] or using autoregressive models [8, 9].

Here the power spectrum is computed from the preprocessed EEG signals using the Fourier Transform in windows of $256\,ms$ (128 samples) with 50% overlap. For each window the average power in the frequency band between $8\,Hz$ and $15\,Hz$ is obtained and the resulting time course is then smoothed.

4.4 Phase-Locking Factor Features

Given two oscillators with phases $\phi_i[n]$ and $\phi_k[n]$, $n = 1, ..., N$, the PLF is defined as [10]:

$$\varrho_{ik} = \left| \frac{1}{N} \sum_{n=1}^{N} e^{j(\phi_i[n]-\phi_k[n])} \right| \tag{1}$$

This measure ranges from 0 to 1. While the value $\varrho_{ik} = 1$ corresponds to perfect synchronization between the two signals (constant phase lag), the value $\varrho_{ik} = 0$ corresponds to no synchronization (phases are not correlated). Put simply, the PLF assesses whether the difference between the phases of the oscillators are strongly or weakly clustered around some angle in the complex unitary circle. In this work, the phase information is extracted from the EEG signals through the concept of Analytical Signals, which is done by applying the Hilbert transform to the signal.

As the PLF is a measure between two signals, 37 pairs of EEG channels were selected. Each pair was processed with a sliding window of $256\,ms$ (128 samples) with 50% overlap. In each window, the phases were extracted from both signals of the pair (through their analytical signals), and the PLF was computed between them. This implies that, for each window of the pair's signals, there is one PLF value. The resulting time course is also smoothed.

4.5 Classification

The identification of ERD in a motor task trial is done using a thresholding technique, applied to the features' time-course. The threshold is automatically obtained from the mean and variance of the first second of the trail, which is used as a baseline. Note that this technique is intended to find areas of the signal that are significantly below, as measured by the threshold value, the initial one second period, thus identifying ERD. The final outcome of this is that it is now possible to select all the feature vectors that will be used as labeled data for training in the classification step.

The actual classification of the features uses Support Vector Machines (SVMs). As the SVM classifier used is defined for a two-class problem, a hierarchical approach was taken to classify the entirety of the seven tasks. The hierarchical classifier, as depicted in Figure 4, uses a sequence of classifiers, with each distinguishing between two classes.

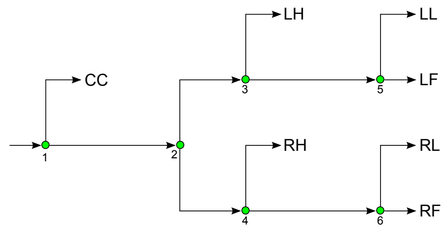

Figure 4: Hierarchical SVM classifier for all classes; green dots represent the SVMs.

In order to evaluate the performance of the classifiers, the Leave-One-Out Cross Validation (LOOCV) method was used. With this method, the training is performed using all but one of the training examples, and the classifier is tested using the excluded sample. This is repeated until all the training examples have been used once for testing. Although the LOOCV method is rather computationally heavy, it allows to train the classifier with the maximum amount of data, and to test it over the entire dataset.

5 Experimental Results

The global accuracy of the classifier, using the LOOCV method, is presented in Table 1, for both types of features and for the actual and imagined movement tasks.

Table 1: Accuracy results (percentage) of the Hierarchical Classifier with both the band power features (BPF) and the PLF features (PLFF), for the actual (Act.) and imagined (Im.) movement tasks.

Subject	**BPF**		**PLFF**	
	Act.	Im.	Act.	Im.
S1	64.24	67.95	87.18	87.54
S2	64.62	65.83	86.99	86.03
S3	75.05	75.92	89.67	87.38
S4	76.81	77.29	84.86	86.30
S5	67.08	74.94	86.45	85.74
S6	64.20	69.25	84.31	85.06
Average	68.67	71.86	86.58	86.34

The results shown in Table 1 allow to conclude that the PLF features are better, with an average accuracy of 86.6% and 86.3%, for the actual and imagined tasks, respectively, against an average accuracy of 68.7% and 71.9% for the band power features. This difference is due to the more robust theoretical formulation of the PLF features, which appear to be more immune to noise than the band power features. For these last features it is evident a trend where the imagined tasks produce higher accuracies than the actual tasks. This is probably due to the fact that the trials with actual movement contain more artifacts than the imagined trials, in particular when the subject has to move the legs. This trend is not visible for the PLF features, accentuating the notion that they are less susceptible to noise.

Despite the good results obtained, these could be improved upon if the thresholding method, used to select the time instants when the task is actually being performed, was more robust. Clearly, the weakest point of this thesis is this threshold, as the performance of the classifier is directly dependent on the training and testing data. The reasons for this are three-fold. First, the thresholding method does not use all the available information, being based on a very reduced subset of features. The problem here is that the ERD event is expected to occur in a localized region of the brain, although there is some spreading to other areas. This makes the definition of a single threshold that fits all the motor tasks very difficult. A more clever way of doing this would be the use of some kind of Blind

Source Separation, attempting to separate the information relative to each type of task. Second, the reference segment, i.e., the first second of the trial, is not long enough to obtain good statistics to compute a baseline to be compared with the rest of the trial. And, thirdly, the threshold does not automatically adapt to the signal within the motor task period. Nevertheless, the method served its purpose without the need to use more complex techniques.

6 Conclusion

The most important conclusion to extract from the work developed in this thesis is that a BCI system based on the use of PLF features is better than an equivalent system based on power band features, considering the limited data available. Furthermore, the system is capable of distinguishing between seven different motor tasks, which is unusual for this type of approach. Nevertheless, more research is still needed, and much remains to do in order attain the next step, which is to adapt this system into a real-time, fully functional, application. To do so, some changes would need to be made to the signal processing steps. For instance, all implementations should be as computationally efficient as possible, in order to minimize the response delay of the system. In this respect, the processing window, here chosen with a length of $256\,ms$, should also be smaller, but long enough to provide useful information for the classification. In regard to the training of the classifier, an off-line approach, like the one used here, could be implemented in the beginning of the session, although the acquisition conditions change over time and, therefore, it would be necessary to use an adaptive approach, retraining the classifier as new information arrives. Finally, a good feedback system has to be incorporated in order for the user to understand clearly what the BCI is doing.

In a more general view, this thesis accomplishes its goal of being one last test to the knowledge and experience obtained over the entire Biomedical Engineering course at IST, allowing a smooth transition of to the work market.

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