Supervised Pattern Recognition Techniques for Detecting Motor Intention of Lower Limbs in Subjects with Cerebral Palsy

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***Abstract* — Cerebral Palsy (CP) is one of the major conditions that prevent subjects suffering from having free control over their limbs, currently the use of electroencephalography (EEG) signals to control rehabilitation devices is a very useful alternative. However, these EEG signals are susceptible to noise and a filtering preprocessing is necessary before the feature extraction and classification. There are very good algorithms detecting motor intensities in the upper limbs such as Least Squares Support Vector Machine (LS-SVM) with spectral density characteristics. However, in the present work we propose to determine the algorithms of extraction of characteristics and classification that allow to detect satisfactorily the motor intensities in lower limbs.**

Keywords — Cerebral Palsy, Electroencephalography, Brain Computer Interface, motor intentions, machine learning.

I. Research Problem

Childhood Cerebral Palsy (CP) disorder is one of the main psychomotor impairment causes in most vulnerable population (children between 4 and 18 years old) [1-3]. One of the techniques used to determine motor intention is through the analysis of signals present in brain motor cortex; there are invasive and non-invasive techniques to capture these signals. A non-invasive technique is electroencephalography EEG [4], however, this technique is susceptible to electrical noise, or artifacts, from relative movements and contact of electrodes, blinking, muscle activity, heart rate, environmental electromagnetic signals, among others. [5, 6].

Techniques for capturing motor cortex activity in the lower limbs are difficult to detect because are generated in central motor gyro located on the inner side of the longitudinal fissure, in primary motor cortex [7]. The research on motor cortical activity is mainly focuses on the analysis of upper limbs in children with CP only [8-11]; likewise, it is not motor cortex activity in lower limbs of subjects with CP based on electroencephalography for Brain Computer Interface EEG-BCI [12].

Additionally, motor cortical activity in subjects with CP (Hemiplegia, Diplegia and Quadriplegia) is proportionally affected to Gross Motor Function Classification System (GMFCS) [8, 11, 13-16]:

I. Almost normal motor function.

II. Independent march, but limitations for running and jumping.

III. The subject is assisted by devices for the walk and wheelchair for long distances.

IV. The subject can stand up for transfers, but has minimal ability to walk, uses a wheelchair to move.

V. Lack of head control, can't sit independently, is dependent on all aspects of care.

Therefore, signals obtained from EEG from this motor region are complex to interpret and understand. Lee et al, demonstrated that cortical upper limbs activity in subjects with a CP level greater than III has activity in irregular cortical areas [11], accordingly, in this dissertation proposal we will focus on subjects who possess residual motor skills type I, II and III According to GMFCS, facilitating the acquire and interpret of EEG signals [5].

II. Outline of Objectives

As a general objective, it is desired to detect lower limb motor intentions using supervised pattern recognition techniques and non-stationary characterization of signals for the computerized care of subjects with CP that could be used in EEG-BCI.

The specific objectives are:

1. To implement an experimental methodology based on EEG-BCI that allows to detect motor cortical activity of subjects with CP when performing lower limb motor intention tasks.
2. To adapt the current characterization algorithms used in EEG-BCI, to extract adequate lower limb motor intentions features.

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3. To develop a methodology, based on supervised classification algorithms used in EEG-BCI, to perform an efficient detection of lower limb motor intentions.

III. State of the Art

The most affected population, by some type of disability, is children between 4 and 18 years old and adults over 30 years old [17]. Childhood Cerebral Palsy (CP) disorder is one of the main causes of psycho-motor impairment in the patient, with children being the most vulnerable population [1-3]. There are rehabilitation techniques that improve the abilities of subjects with CP [13]. These include upper and lower limb motor tasks, taking advantage of cerebral plasticity, especially in the child population to improve the performance of the cortical activity in patients [18, 19]. Cerebral plasticity has a better performance in children while the patient has residual motor skills [8, 20].

Brain plasticity plays an important role in rehabilitation [21-24] and even more in children [8, 18-20], improving their motor and sensory coordination performance [8, 20]; but these therapies usually use biosignals generated by muscle activity in small proportions such as electromyography (EMG) signals, being a problem for people who have been born with motor problems and without muscular tone [13, 25, 26]. Therefore, the use of non-invasive techniques using surface electrodes distributed with the "International System 10-20" [27], to obtain electrical EEG activity in the brain, is one of the most commonly used non-invasive techniques in BCI (EEG-BCI), which requires less equipment and, therefore, is an economic alternative [4, 28] applicable in rehabilitation therapies [12, 29].

Brain Computer Interfaces (BCI) allow subjects with CP to interact with devices that help them to perform muscle tasks [13, 25, 26]. The motor cortical activity measured with EEG-BCI systems is most evident in the frequency band of 13-30 Hz, or β band, and in the frequency band of 8-12 Hz, or μ band [5]. Generally, the techniques used to determine motor intentions in these frequency ranges (β and μ) are: Power Spectral Density (PSD) measurement [33-35], measurement of Event Related Potentials (ERP) [36], particularly to the 300 ms (P300) [36, 37], the Event Related Desynchronization (ERD) and Event Related Synchronization (ERS), characteristic relationship defined as ERD/ERS [10, 38, 39], which allows visualization of cortical motor activity [40]. These features have been evaluated in studies of subjects with CP during upper limb motor tasks [33, 41, 42], and have shown that motor cortical activity is irregular and the subject's gross motor ability becomes chaotic [11].

Currently, the use of big data analysis techniques based on Computational Intelligence and automated learning algorithms (supervised and unsupervised), allow us to extract features and classify the motor intentions of patients [33,43-50]. For example, some of the techniques used in classification are Support Vector Machine (SVM) [47, 51], Artificial Neural Networks (ANN) [48-50, 52], or Linear Discriminant Analysis (LDA) [33]. According to [33, 41, 42] SVM has been shown to perform better in the classification of upper limb motor intentions, the comparison of the algorithms is shown in Table I.

Table I. BCI-EEG Classification algorithm comparison [33, 41, 42].

Compare Criteria	**Feature**	**Classification Result**
Accuracy (%)	PSD	LS-SVM > Linear-SVM > PNN > MLNN > LVQ
		Linear-SVM > LDA
	ERD/ERS	Linear-SVM > ELM > LDA
		Adaboost-ELM > Adaboost-SVM > Adaboost-LDA
Computational time (s)	PSD	LS-SVM < PNN < LVQ < MLNN < Linear-SVM

IV. Metodology

The research will be carried out in 5 stages:

A. *Experiment design*

At least 10 subjects with CP (Hemiplegia, Diplegia and Quadriplegia) of type I, II and III without surgery, younger than 16 years old are expected to participate, with prior written consent of their families and Ethics Committee. The experiments will be performed at the Teodoro Maldonado Carbo Hospital (HTMC) in the Guayaquil city, which has a Neurophysiology laboratory with installed capacity to measure EEG signals [51]. The subject will be seated in a comfortable chair, while a computer screen indicates randomly the tasks to perform:

- Motion Execution (ME): The subject makes an extension of the upper or lower limb, lifting the limb comfortably as possible. Then, the subject must flex the upper or lower limb to bring it to the original position [8, 41].
- Kinesthetic-Motor Images (KMI): The subject should imagine the movement of the limb until reaching the extension of the upper or lower limb and its posterior flexion, based on the kinesthetic experience in the ME exercise [8].
- Observation of the Movement (OOM): The subject on a computer monitor will only observe the animation of extension and flexion of the upper or lower limb [8].
- Motor Visual Images (VMI): The subject will mentally reproduce the animation of extension and flexion of the upper or lower extremity seen in OOM exercise [8].

These tasks will be combined with the following instructions: Right Hand, Left Hand, Both Hands, and Both Feet [55-57]. Each task will last 6s, followed by a 10s rest, allowing the subject to relax and avoid possible fatigue. During a run, each subject will perform twice all tasks. Ideally, there will be 5 runs for each subject [57].

B. *Data collection*

Data collection will be performed with subjects who have residual motor skills to perform motor intention tasks [5]; Therefore, this activity will be developed with patients with CP (Hemiplegia, Diplegia and Quadriplegia) of type I, II and III; According to GMFCS [13-16].

C. Pre-processing of data

EEG data acquired by superficial methods are very susceptible to noise, or artifacts [5, 6]. Pre-processing aims to reduce the Signal-to-Noise Ratio (SNR) of EEG data in the range of 0.1 - 60 Hz [54] (μ and β rhythms); For this purpose, we will use, bandpass filters of constant coefficients (Buttherworth-IIR or Wiener-FIR) [5] using the Biosig-Toolbox and Matlab as programming language [9].

The filtered EEG signals will be segmented manually into temporary windows of 6 seconds [52]. Each temporary window represents one of the tasks: ME, KMI, OOM and VMI.

D. Signal Characterization

In the brain, all mental tasks and especially MI have different powers in the frequency range of the μ and β rhythms [54]. Therefore, it will be started using two of the methods suggested by the literature for the extraction of features in BCI applications:

- Weltch or Power Spectral Density (PSD) periodogram, which will allow us to have the power distribution of the signal as a function of frequency [33-35].
- Event Related Desynchronization (ERD) and Event Related Synchronization (ERS), or also called (ERD / ERS); is a characteristic related to Sensorimotor Rhythms (SMR) [9, 10, 28, 38-41, 57, 96].

E. Features Selection

In EEG-BCI applications, combining different types of features, gives us redundant data of high dimensions that does not contribute to the classifier. S. Mozaffar and R. Chai in [45, 46] respectively, suggest using Independent Component Analysis (ICA), as it improves the performance of classification algorithms by ensuring that the features delivered are statistically independent and do not have redundant information [44]. However, there are many optimization techniques based on genetic algorithms (GA) [44], which should be explored in the development of research.

F. Classification

Among the most used algorithms in BCI applications, for recognition and classification EEG patterns of upper limb intentions, we will start using the following methods:

- Least Squares Support Vector Machine (LS-SVM) with PSD features, as it has a better success rate than Linear Discriminant Analysis (LDA) [42] and Artificial Neural Network (ANN): Probabilistic Neural Network (PNN), Multilayer Neural Network (MLNN), Learning Vector Quantization (LVQ) [33].
- Linear-SVM with PSD and ERD/ERS features, because it has a better success rate than Extreme Learning Machine (ELM) and LDA [41, 42].
- The Adaboost model (developed by Freund and Schapire) that allows to classify classifiers [58, 59] as Extreme Learning Machine (Adaboost-ELM) has demonstrated that with ERD/ERS features it is more accurate classifying MI-EEG signals than Adaboost-SVM and Adaboost-LDA [41].
- Artificial Neural Network (ANN) with ERD/ERS features, in spite of having a low rate of success than LS-SVM and Linear-SVM, we want to determine their performance in the lower limb [33].

V. Expected Outcome

This research looks for answering the following research questions:

1. What is the methodology and experimental design for obtaining lower limb motor cortex activity based on EEG-BCI for subjects with CP?
2. Which will be characterization algorithms used in EEG-BCI, allow to extract adequate features of motor intentions of lower limbs?
3. What should be the methodology, based on selected supervised classification algorithms used in EEG-BCI, to perform an efficient detection of lower limb motor intentions?
4. How could identify the cortical regions involved during the execution of lower limb motor intentions, for each type of CP?

VI. Stage of the Research

CP disorder represents one of the main causes of disability affecting the quality of life of people and their families who should dedicate time to their care with a direct impact on the family economy and its relationship with the society [3]. Also, statistics from the World Health Organization (WHO) [62], show that CP is the major cause of physical disability in the population of children between 4 and 18 years, and adults over 30 years [8]. Worldwide prevalence of CP is 1.5 - 5.6 cases per 1,000 live births [13, 26, 61].

The therapeutic techniques used to improve postural control and balance for CP subjects have: Virtual Reality (VR) in interactive games [63,64], therapy / assisted activities with horses [65,66], and treadmill training [67,68]. In addition, there are less frequently used rehabilitation techniques that they use: psychomotricity program [69], task training aimed at improving balance [70], healthy-side movement restriction therapy [71], progressive resistance training [72], functional electrostimulation [73], ground or pool kinesitherapy [2] and whole-body vibration [74]. Of the techniques mentioned, treadmill training (with or without partial weight support) has been shown to be more effective than the application of conventional physiotherapy [2].

Most PC subjects do not have the ability to control their extremities and the measurement of biomedical signals that allow them to control devices for rehabilitation such as exoskeletons in treadmills [67, 68], becomes difficult. Unlike EMG signals that require muscular effort to generate biosignals [25, 26], EEG alone with imaging movements generates bioelectric activity that can be used in the control of these devices [75].

EEG signal data acquired during the execution of motor intensities of upper and lower extremities in healthy subjects, was obtained on the *PhysioNet* website (http://www.physionet.org/physiobank/ database / eegmmidb /), these data were acquired using a BCI2000 system, available in the European Data Format (EDF) format [57]. As part of this research, EEG signal data should be collected in subjects with CP type I, II and III; According to GMFCS [13-16].

In the detection of upper limbs motor intensities, the LS-SVM algorithm with PSD features has a better success rate with a shorter processing time than Artificial Neural Networks [33]; And Adaboost-ELM with ERD/ERS features has a better success rate than Adaboost-SVM and LDA [41]. For the detection of upper limbs motor intensities, it is justified to carry out research that allows us to detect the patterns of motor cortical activity of subjects with CP; To propose the development of algorithms that allow us to extract adequate characteristics of the motor intentions of lower limbs; And, develop effective supervised classification algorithms for the EEG-BCI analysis.

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