Cerebral Palsy EEG signals Classification:

Facial Expressions and Thoughts for Driving an Intelligent Wheelchair

Brigida Monica Faria
DETI/UA – Dep. Electrónica, Telecomunicações e Informática/UA and ESTSP/IPP – Escola Superior de Tecnologia da Saúde do Porto / Instituto Politécnico do Porto
Aveiro and Porto, Portugal
btf@estsp.ipp.pt

Luis Paulo Reis
EEUM – Escola de Engenharia da Universidade do Minho, Departamento de Sistemas de Informação and LIACC – Laboratório de Inteligência Artificial e Ciência de Computadores, Univ. do Porto
Guimaraes and Porto
lpreis@dsi.uminho.pt

Nuno Lau
DETI/UA – Dep. de Electrónica, Telecomunicações e Informática / Universidade de Aveiro and IEETA – Instituto de Engenharia Electrónica e Telemática de Aveiro
Aveiro
nunolau@ua.pt

Abstract—**Brain Computer Interfaces (BCI) enables interaction between users and hardware systems, through the recognition of brainwave activity. However, the current BCI systems still have a very low accuracy on the recognition of facial expressions and thoughts. This makes it very difficult to use these devices to enable safe and robust commands of complex devices such as an Intelligent Wheelchair. This paper presents an approach to expand the use of a brain computer interface for driving an intelligent wheelchair by patients suffering from cerebral palsy. The approach was based on appropriate signal preprocessing based on Hjorth parameters, a forward approach for variable selection and several data mining algorithms for classification such as naive Bayes, neural networks and support vector machines. Experiments were performed using 30 individuals suffering from IV and V degrees of cerebral palsy on the Gross Motor Function (GMF) measure. The results achieved showed that the preprocessing and variable selection methods were effective enabling to improve the results of a commercial BCI product by 57%. With the developed system it was also possible for users to perform a circuit in a simulated environment using just facial expressions and thoughts.**

Keywords – Brain Computer Interface; Cerebral Palsy; Intelligent Wheelchairs; Facial Expressions; Thoughts.

I. INTRODUCTION

The studies of the electrical signals produced by the brain are addressed both to the brain functions and to the status of the full body [1]. By applying digital signal processing methods to the electroencephalogram (EEG) signals obtained by the brain activity it is possible, for example, to obtain patterns for diagnosis and treatment of brain disorders.

The beginning of research in terms of number of electrical signals emitted by the nerves of the muscles goes back to the nineteenth century with Carlo Matteuci and Emil Du Bois Reymond [2]. Although the research in this area never stopped, the first experiments of EEG on humans belong to Hans Berger in 1929. Besides all the interesting research approaches he also found the correlation between the mental activities and the changes in the EEG signals making possible the creation of new human-machine interactions. The communication devices based on EEG are known today as Brain-Computer Interfaces (BCI), mostly based on the research developed in the seventies at the University of California, Los Angeles and consequently scientific papers that marked the first appearance of the Brain-Computer Interface research area in the literature [3] [4].

Cerebral Palsy (CP) is the term used for a group of non-progressive disorders of movement and posture caused by abnormal development of, or damage to, motor control centers of the brain. CP is caused by events before, during or after birth [5]. The abnormalities of muscle control that define CP are often accompanied by other neurological and physical abnormalities [6]. These physical constraints limit the daily life in terms of independence and autonomy. Therefore it is necessary to develop assistive technologies to minimize mobility problems and to overcome some restrictions of patients.

Assistive Technologies are defined as any product, instrument, equipment or adapted technology specially planned to improve the functional levels of the individual with deficiency [7]. Wheelchairs are examples of this kind of products. The evolution of wheelchairs allows today having more sophisticate equipment and interfaces. The term intelligent wheelchair is more common and in the scientific community more attention is given to these brands of instruments. However most of the studies do not include experiments with real patients and the works are confined to the research labs.

The work presented in this paper combines the knowledge discovery process, more precisely the process of acquiring and selecting variables, the experiments with real patients and the integration of a brain computer interface that allows driving an intelligent wheelchair.

The paper is organized as follows. After this introductory section, the second section describes the BCI concept and the state of art of applications made using intelligent wheelchairs. The third section briefly describes our intelligent wheelchair project and our approach on applying knowledge discovery techniques to improve the use of facial expressions and thoughts as inputs for driving an intelligent wheelchair. Experiments and results are presented at section four and finally conclusions and future work are presented in the last section.

II. Brain Computer Interface

A Brain Computer Interface (BCI) is a type of device which allows interaction between users and computer systems, through the recognition of brainwave activity. Normally, brain computer interfaces are used in medical contexts, with the objectives of augmenting cognitive and sensory-motor functions. BCIs can be classified in different categories [8]:

- Invasive/Non-Invasive - this classification refers to how the BCI is placed to obtain the brain activity. Invasive and partially-invasive BCIs require medical and surgical intervention, since they are implanted in the user's brain. Non-invasive BCIs do not require brain implants. However, non-invasive BCIs are less effective when compared to invasive BCIs, since the obtainable signal of brainwave activity is weaker.
- Dependent/Independent – if a BCI involves a certain level of motor control from the user it is called a dependent BCI. On the other hand if it is not necessary any motor control from the users it is called an independent BCI.
- Synchronous/Asynchronous - the computer drives synchronous systems by giving the user a cue to perform a certain mental action and then recording the user's EEG patterns in a fixed time-window. Asynchronous systems are determined by the user and operate by passively and continuously monitoring the user's EEG data and attempting to classify it in the moment.

The next subsections present a brief description of the biological matter of neural activity, the rhythmic that can be acquired and the techniques for measuring the brain activity.

A. *Neural Activity*

The central nervous system (CNS) is the part of the nervous system that integrates the information which is received from all parts of the body and coordinates all the activity [1]. Basically the CNS is made of the brain and spinal cord. It is composed of axons, dendrites and cell bodies. An axon (or nerve fiber) is usually long and thin. Typically, it conducts electrical impulses away from the neuron's cell body. Dendrites are normally shorter, become thinner with distance and are branched projections of a neuron that acts in order to conduct the electrochemical stimulation received from other neural cells to the cell body of the neuron from which the dendrites project [1]. Axons are different from dendrites in several features, including shape, length in which dendrites are restricted to a small region around the cell body while axons can be much longer, and function where dendrites usually receive signals while axons usually transmit them.

Axons make contact with other cells, usually other neurons but sometimes muscle or gland cells, at junctions called synapses. At a synapse, the membrane of the axon closely adjoins the membrane of the target cell, and special molecular structures serve to transmit electrical or electrochemical signals across the gap.

In the human brain each nerve is connected to thousands of other nerves [1]. An EEG signal is the measurements of the activity that flows during the synaptic excitations of the dendrites of many neurons in the brain [1]. When the neurons of the brain are activated the synaptic flow is produced in the dendrites. With this current it is generated a magnetic field which can be measured by an electromyogram or a secondary electrical field over the scalp measured by EEG systems [1].

Since the human head is composed of different layers such as scalp, skull, brain and other kind of thin layers, the signal measured at the scalp is attenuated. For that reason and because of the internal, external and system noises, recording electric measures using the scalp electrodes are only viable in areas of large populations of bouncing neurons. Then it is necessary to amplify these signals in order to display the information [9].

The EEG signals can be recorded from electrodes that are place on the scalp of the human brain. In order to ensure the reliability of the studies in terms of reproducibility over time and subjects it was implemented the International 10-20 system [10].

B. *Intelligent Wheelchairs and Brain Computer Interfaces*

An Intelligent Wheelchair (IW) is a locomotion device to assist a user having some kind of physical disability, where an artificial control system augments or replaces the user control [11][12]. The main objective is to reduce or eliminate the user's task of having to drive a motorized wheelchair. Usually, an IW is controlled by a computer, has a set of sensors and applies techniques derived from mobile robotics research in order to process the sensor information and generate the motors commands.

The idea of integrating brain computer interfaces in intelligent wheelchairs was already present in several works in the literature that explored distinct approaches to this subject. The wheelchair prototype developed by the LURCH project [13] uses a non-invasive BCI that allows the user to drive the wheelchair. By using a headset equipped with a number of electrodes, the user can train thought patterns that will be associated to a certain output action. In spite of being in a premature state of development, this technology might be of good use for medical purposes, namely for severely disabled individuals.

The Maia project is a European project aiming at the development of an electroencephalography-based brain-computer interface for controlling an autonomous wheelchair [14]. The wheelchair control has automatic obstacle avoidance and is also capable of following walls. The user can control the wheelchair movement giving commands such as "go back" or "go right".

Blatt et al. [15] proposed a slightly different approach enabling a user to drive an intelligent wheelchair, using a BCI. In this work, instead of performing high-level commands, the user should continuously drive the wheelchair.

Another project under development at the National University of Singapore consists of an autonomous wheelchair controlled through a P300-based BCI [16]. The main limitation of this project is that the wheelchair movements are limited to predefined paths. The user selects a destination, and the wheelchair automatically calculates the trajectory to the desired place. If an unexpected situation occurs, the wheelchair stops and waits for further commands.

Unfortunately, some problems may arise while trying to use a BCI in a complex task such as controlling a wheelchair. Brain activity varies greatly from individual to individual, and a person's brain activity also changes substantially over time [17]. These obstacles make it difficult to develop systems that can easily understand the user intentions, especially for long periods of time. Also, long periods of training are necessary before a user can correctly use a BCI to control a specific device [17].

The group of patients suffering from cerebral palsy is also very challenging. Although it is possible to make a classification of the level of severity, people suffering from cerebral palsy are very heterogeneous. However, most of the work and applications of brain computer interfaces to drive wheelchairs do not consider the specificities of this population which needs this kind of assistive technology.

III. Knowledge Discovery and EEG Applications for Driving an Intelligent Wheelchair

A. IntellWheels Project

The IntellWheels project consists of an intelligent wheelchair platform that may be easily adapted to any commercial wheelchair and aid any person with special mobility needs [18] [19]. The first prototype developed was focused on the development of the modules that provided the interface with the motorized wheelchair electronics using a portable computer and other sensors. Several different modules have been developed in order to allow different ways of conveying commands to the intelligent wheelchair. A multimodal interface was developed to drive the IW as can be observed in Figure 1. There are several inputs that allow this such as voice commands, joystick, buttons and head movements [20]. It is also possible to combine all the inputs, for example it is possible to push a button and say “go” for the IW follow right wall. Recently it was integrated a brain computer interface (Emotiv System [21]) enabling to drive the IW also with facial expressions and thoughts.

Regarding the use of facial expressions to control the IW, from the multimodal interface perspective, only the expression identified is acquired, along with the system uptime, but in order to connect the BCI to the multimodal interface application, an additional application was necessary [22]. On this bridge application it is possible to collect data from several variables. This bridge application connects to the multimodal interface as a client and sends the recognized facial expressions to be used as inputs in the multimodal interface. This allows associating a high-level order to an expression or sequence of expressions on the multimodal interface. The bridge application accepts the facial expression recognized as valid, if during a defined period of time the expression is detected a certain amount of time with a recognition percentage that exceeds a defined threshold.

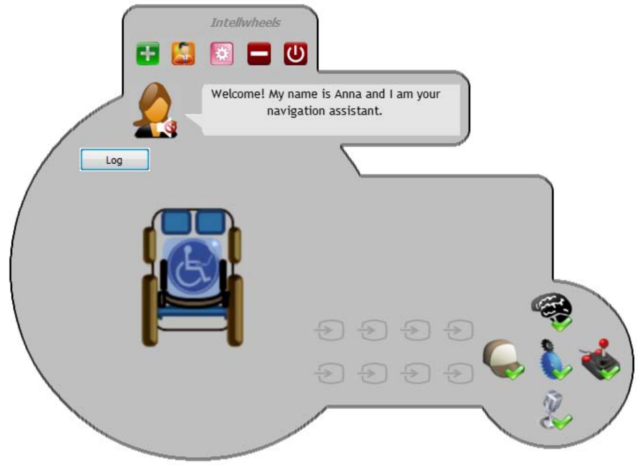

Figure 1. Intelligent Wheelchair Multimodal interface.

However, the accuracy for identifying expressions and thoughts is very low with users suffering from cerebral palsy. For that reason it was acquired the raw data and several techniques were applied such as preprocessing techniques and variable selection and data mining in order to produce a better model for classification.

Besides constructing the real prototype, a simulator was also developed in the context of IntellWheels project [20]. All the characteristics and motions of the real IW could be performed in a very similar way in the simulated environment. On the simulator, an intelligent wheelchair was modeled including exactly the same sensors as the real wheelchair. This enabled to use the multimodal interface to control both the real and simulated wheelchair just changing a simple configuration parameter. Figure 2 shows the real and the simulated prototype of the intelligent wheelchair.

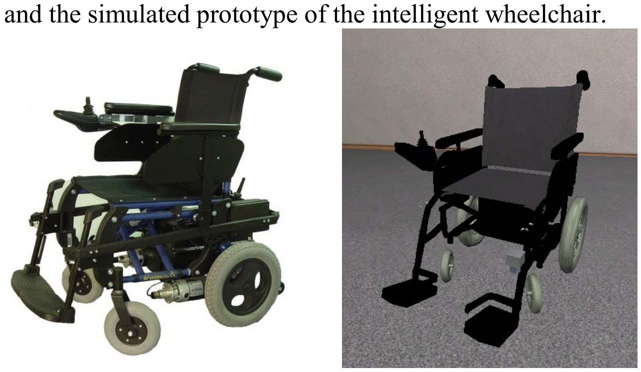

Figure 2. Real prototype (a) and simulated model (b) of the intelligent wheelchair.

The importance of the simulator is huge, since it enables to test algorithms and methodologies in a safe and low cost manner.

B. Approach for applying EEG signals

One of the main objectives of using EEG signals may be to facilitate the communication between a machine and people with severe limitations. The process of EEG based control should follow several phases to give the commands to the controller. The phases can be integrated in the process of knowledge discovery.

1) EEG data acquisition and data selection

The data acquisition was made using a brain computer interface available for research edition: Emotiv System [21] [23].

The headsets are wireless and use a proprietary USB dongle to communicate using the 2.4GHz band. The headsets contain a rechargeable 12 hour lithium battery, 14 EEG saline sensors and a gyroscope.

The Software Development Kit (SDK) used was the Research SDK Edition. The description of the techniques applied on this commercial version for recognizing thoughts and facial expressions are not available. Only a general description of the methods can be found in the manual [23] and explanations in the official forum [21]. However the raw EEG data from the device can be acquire and analyzed enabling researchers to develop their own facial expressions/thoughts recognition methods.

The data received by the Emotiv headset basically comes from 14 EEG channels and from the values of the gyroscope. In Fig. 3 it is possible to verify in the 10-20 International System the EEG channels that are included in Emotiv headset (signaled in grey).

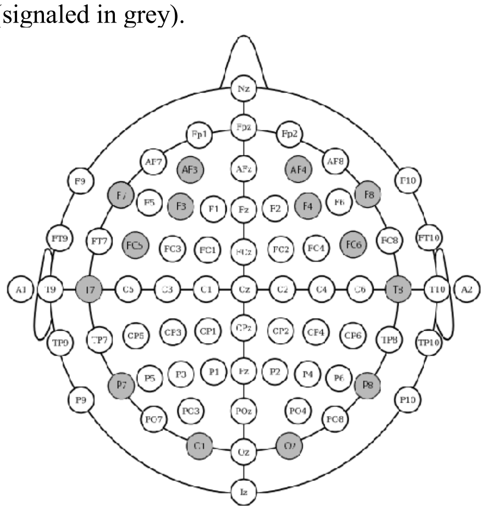

Figure 3. EEG channels available in the Emotiv [Adapted from [23]].

The data selected to be analyzed are the raw data from each sensor: AF3; F7; F3; FC5; T7; P7; O1; O2; P8; T8; FC6; F4; F8; AF4, the values from the gyroscope and the timestamp. The EEG signal units are microvolts and the sampling rate is 128 Hz. There is also a partial sampling between seconds in which is given information about all the variables. The variables GYROX and GYROY are horizontal and vertical accelerations from the gyroscope.

This data refers to several facial expressions and thoughts. The initial set of facial expressions is: smile; left smirk; right smirk; blink the eyes; blink the left eye; blink the right eye; furrow; clench; eyebrows and normal. The possible thoughts asked are: forward; back; left; right; left spin and right spin. Fig. 4 shows graphical examples of the raw data by some of the facial expressions acquired from the patients.

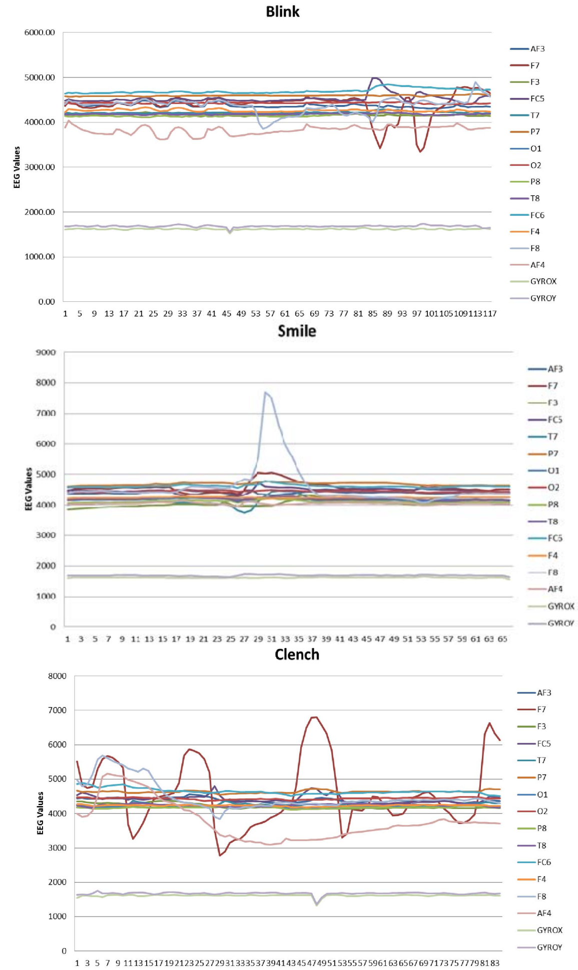

Figure 4. Examples of the values of the EEG channels by facial expression.

It is clear a different pattern of the EEG values during the time of each facial expression. To extract the final features for classification it was necessary to perform preprocessing.

2) Preprocessing

Several steps were performed in this phase of preprocessing. Fig. 5 shows a general overview of these steps.

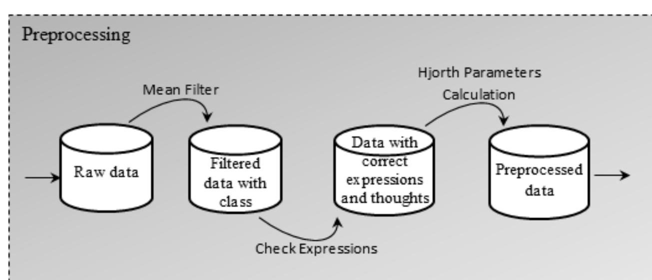

Figure 5. Overview of the preprocessing stages.

The first step in preprocessing was to apply a mean filter to the partial sampling of the EEG sensors as in (1) and Gyroscope as in (2):

$$\overline{x}_{EEG^j} = \frac{1}{k}\sum_{i=1}^{k} EEG_i^j \quad (1)$$

$$\overline{x}_{Gyr^j} = \frac{1}{k}\sum_{i=1}^{k} Gyr_i^j \quad (2)$$

where k = 0, …,$n_{\text{partial sampling}}$ and j is the timestamp that correspond to a facial expression or thought. It was necessary to check if the expressions were performed correctly.

Next, in order to extract the features, the Hjorth parameters [24] for each expression and thought were calculated. The Hjorth parameters [25] present three measures to characterize the EEG signals in terms of amplitude, time scale and complexity [26]. These parameters can discriminate between mental states. The parameters are:

Activity (*Ac*) – it is a measure of the mean power of the signal. It is measure using the standard deviation of the signal:

$$S_{Ac}^i = \frac{1}{l}\sum_{i=1}^{l}(S^i - \overline{S}^i) \quad (3)$$

where l is the amplitude of time corresponding to the facial expression or thought; i=1,…16 and S is the signal.

Mobility (*Mo*) – it represents the mean frequency in the signal. This measure can be calculated as the ratio of the standard deviation of the slope (S_d^i) and the standard deviation of the signal as in (3)

$$S_{Mo}^i = \frac{S_d^i}{S_{Ac}^i} \quad (4)$$

Complexity (*Co*) – the objective with this measure it is to capture the deviation from the sine wave (the softest possible curve). It is expressed as the number of the standard slopes actually seen in the signal during the average time required for one standard amplitude deviation. Equation 5 allows calculating the complexity:

$$S_{Co}^i = \frac{S_{dd}^i}{S_{Ac}^i} \quad (5)$$

where S_{dd}^i is the standard deviation of the second derivative of the EEG signal.

At this stage the dataset as composed of the Hjorth Parameters for all EEG and gyroscope values as features and the class composed of all valid expressions and thoughts.

After the first experiments it was also necessary to apply an optimized selection of variables eliminating irrelevant and redundant features. Fig. 6 shows an example of the variation of the Hjorth parameters and the differences between each facial expression using the error bars.

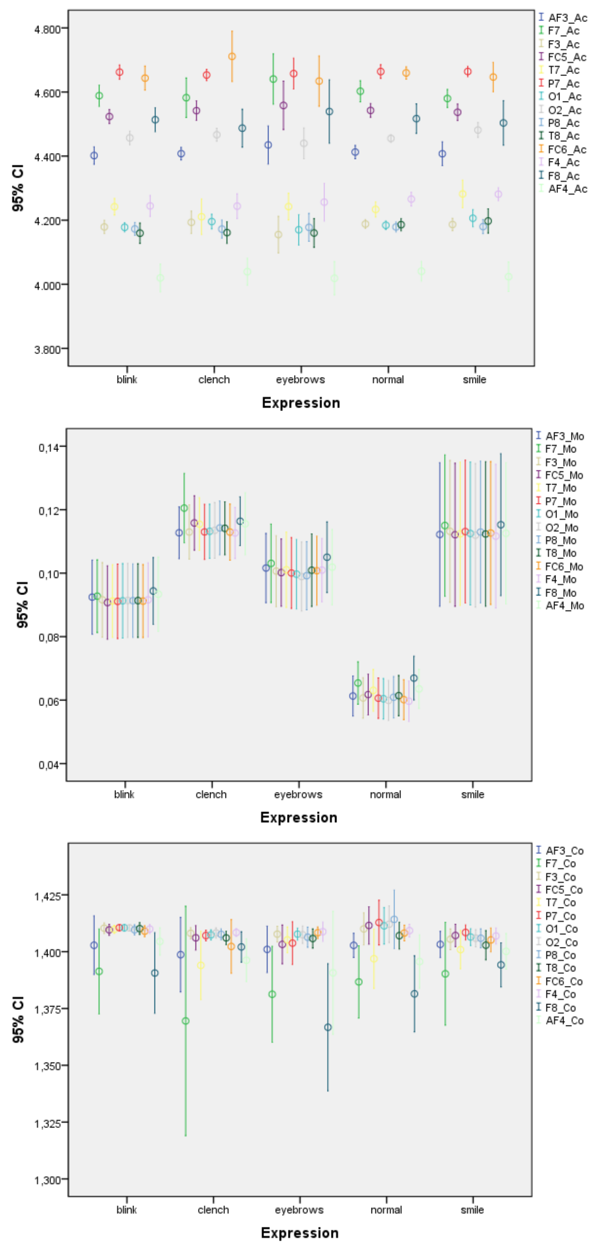

Figure 6. Visualization of different patterns of facial expressions using the Hjorth parameters.

Therefore the procedure of optimized selection of variables performs feature selection algorithm with forward selection. The implementation was developed using RapidMiner [27].

The forward selection is characterized for starting with an empty selection of attributes and, in each round, it adds every one unused attribute of the given set of examples. For each added attribute, the performance is estimated. Only the attribute giving the highest increase of performance is added to the selection. Then a new round is started with the modified selection.

Finally it was tested with 10-fold cross-validation the best performance of models achieved by the techniques of data mining for multiclass classification.

IV. Experiments and Results

An application was implemented in order to record the raw data from the sensors as can be observed in Fig. 7. The methodology consisted in asking to users with cerebral palsy to mimic several facial expressions. An occupational therapist was involved in the process and responsible for verifying if the facial expressions were performed correctly. This information was added to the data and only the correct expressions were added to the final data set.

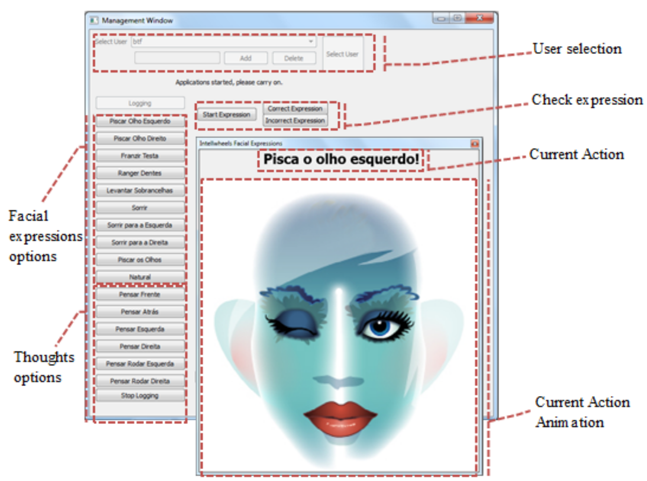

Figure 7. Manager to log the facial expressions and thoughts

The individuals included in this study suffer from cerebral palsy and were classified in the levels IV (23%) and V (77%) of the Gross Motor Function Measure [28]. These are the highest levels in the cerebral palsy severity degree. The sample size was composed of the 30 individuals and all require the use of a wheelchair. The mean of age was 28 years old with 73% males and 27% females. In terms of school level 36% just have the elementary school, 27% have the middle school, 27% have the high school and only 10% have a BSc. The dominant hand was divided as: 50% for left, 33% for right hand and 17% did not answer. The aspects related to experience of using manual and electric wheelchair were also questioned. Table I shows the distribution of answers about autonomy and independency using the wheelchair and constraints presented by these individuals.

TABLE I. Experience using wheelchair, Autonomy, Independence and Constraints of the cerebral palsy users

Experience, Autonomy, Independence and Constraints			
Variables	***n***	***Variables***	***n***
Use manual wheelchair		Cognitive constraints	
yes	10	yes	16
no	20	no	14
Use electric wheelchair		Motor constraints	
yes	22	yes	100
no	8	no	0
Autonomy using wheelchair		Visual constraints	
yes	23	yes	14
no	7	no	16
Independence using wheelchair		Auditive constraints	
yes	23	yes	0
no	7	no	30

The data set for constructing the classification model has five facial expressions types. In fact, the individuals could not correctly perform the left and right smirks. The number of samples of furrow, left blink and right blink was very low and for that reason were also eliminated from the dataset. The number of examples by each facial expression is: 20 blink; 20 clench; 14 eyebrows; 23 smiles and 30 with the natural facial expression. In terms of thoughts all 30 examples by each though were considered.

The experiments were divided in two parts: the model for the facial expressions and the model for the thoughts. In each task it also performed the analysis of the accuracy with and without preprocessing. The data mining algorithms applied for comparison were: Naïve Bayes; Support Vector Machines, Neural Networks, Nearest Neighbour and Linear Discriminant Analysis. The evaluation was made using the 10-fold cross validation. Table II presents the results achieved without optimized selection of variables.

TABLE II. Accuracy and Parameters for Facial Expressions and Thoughts without selection of variables

Accuracy of models without optimized selection of variables			
Algorithms	***Acc (%) Expressions***	***Acc (%) Thoughts***	***Parameters***
Naïve Bayes	36,36	15,79	laplace correction
Support Vector Machines	28,73	15,70	kernel type=radial basis function; epsilon=0.001
Neural Netwoks	35,27	18,39	training cycles=500; learning rate = 0.3; momentum=0.2
k-Nearest Neighbour	17,64	8,68	k=4; mixed measure=mixed euclidean distance
Linear Discriminat Analysis	25,91	23,19	---

The results are significantly better with an optimized selection of variables, where an application of neural network can achieve 55% of accuracy (Table III). The results of thoughts accuracy also increase, however are still very low.

TABLE III. Accuracy and Parameters for Facial Expressions and Thoughts with Preprocessing

Accuracy of models with preprocessing			
Algorithms	***Acc (%) Expressions***	***Acc (%) Thoughts***	***Parameters***
Naïve Bayes	54,64	23,22	laplace correction
Support Vector Machines	43,55	26,96	kernel type=radial basis function; epsilon=0.001

Accuracy of models with preprocessing			
Algorithms	***Acc (%) Expressions***	***Acc (%) Thoughts***	***Parameters***
Neural Netwoks	**55,36**	**27,57**	training cycles=500; learning rate = 0.3; momentum=0.2
k-Nearest Neighbour	55	25,56	k=4; mixed measure=mixed euclidean distance
Linear Discriminat Analysis	54	25,94	---

The final experiments included both the simulator and the shared control. It was modeled a similar scenario of the institution where the patients used to be and it was tested the behavior of the IW with the facial expressions and thoughts.

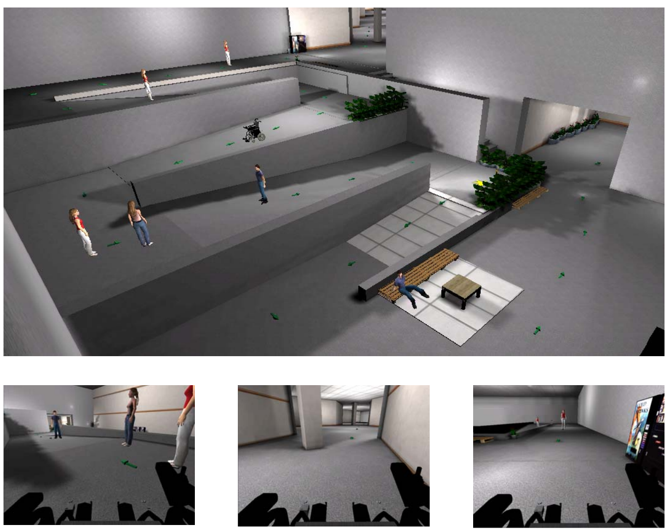

Figure 8. Snapshot of the cerebal palsy center modelled where the tests were performed (top) and three first person view snapshots (bottom).

Ten trials were performed with real users in order to test the system. The tests showed that it was possible to complete the circuit using only facial expressions and thoughts as the wheelchair inputs. The mean time for doing the circuit using other kinds of input methods was 1’53’’ (with a standard deviation of 1.4 seconds). With facial expressions the average time was 5’42’’ with a standard deviation of 9.2 seconds. Finally using only thoughts as the wheelchair input method, the average time necessary was 12’13’’ with 17.7 seconds of standard deviation. Although it was possible to complete the circuit using thoughts, this input method is still far from being comfortable to enable driving in a robust manner, an intelligent wheelchair. However, there are patients, in the group used for the tests, that are completely unable to use any other kind of method for driving the wheelchair in a robust manner. Thus, this method, although not comfortable, may still be very useful.

V. Conclusions and Future Work

The population using electric or manual wheelchairs is very high in the group of patients suffering from cerebral palsy. The wheelchairs are very important assistive technologies to autonomy and independence. However there is a group that necessity particular adaptation. In fact there are cases which do not have cognitive deficits but severe physical handicaps.

This paper presents an approach that provides a platform that could be adapted to any electrical wheelchair and where it was integrated a multimodal interface. The objective of this multimodal interface is to give the best choice to a user for driving the wheelchair. Since there are patients with severe physical problems a brain computer interface was integrated in the multimodal interface. After the first experiments and as expected, the low accuracy of facial expression and thoughts recognition was shown. However, using the raw data provided by the EEG sensors, applying appropriate signal preprocessing based on Hjorth parameters, a forward approach for variable selection and using a neural network it was possible to verify a substantial improvement on the facial expressions recognition. This enabled to drive the wheelchair using only facial expressions and thoughts.

For future work more data is going to be collected in order to provide better classification models. An interesting point to be tested is concerned with the adaptation of the language for each user. This means that if a user only can perform a single facial expression such as smiling or this is the only expression that the classification model can accurate predict, the concept of sequence associated to an action is going to be applied using only the robustly detected expressions. For example, smiling once may be associated with going forward and smiling twice may be associated with turning right. We believe that this will enable even patients with very severe cerebral palsy, Parkinson disease or even Moebius syndrome to drive our intelligent wheelchair.

Acknowledgments

This work was funded by the ERDF – European Regional Development Fund through the COMPETE Programme (operational programme for competitiveness) and by National Funds through FCT - Portuguese Foundation for Science and Technology within project «INTELLWHEELS - Intelligent Wheelchair with Flexible Multimodal Interface, RIPD/ADA/109636/2009». The first author would like to acknowledge also FCT for the PhD Scholarship FCT/SFRH/BD/44541/2008.

References

[1] S. Sanei and J. Chambers, EEG Signal Processing, England: John Wiley & Sons, Lda, 2007.

[2] C. Zywietz, A Brief History of Electrocardiography - Progress through Technology, Hannover: Biosigna Institute for Biosignal Processing and Systems Research, 2003.

[3] J. Vidal, “Toward direct brain-computer communication,” Annual review of biophysics and bioengineering, 1973, pp. 157-180.

[4] J. Vidal, “Real-Time Detection of Brain Events in EEG,” IEEE Proceedings, vol. 5, no. 65, 1977, pp. 633-641.

[5] P. Rosenbaum and D. Stewart, “The world health organization international classification of functioning, disability, and health: a model to guide clinical thinking, practice and research in the field of cerebral palsy,” Seminars in Pediatric Neurology, vol. 11, no. 1, March 2004, pp. 5-10.

[6] Farlex, "Cerebral Palsy," 2010. [Online]. Available: http://medical-dictionary.thefreedictionary.com/Cerebral+Palsy. [Accessed February 2012].

[7] T. Fernandes, "Independent mobility for children with disabilities." International Journal of Therapy & Rehabilitation. July; vol. 13, no. 7, pp 329 – 333, 2006.

[8] A. Cabrera, Feature Extraction and Classification for Brain-Computer Interfaces, Aalborg: Aalborg University, Denmark, 2009.

[9] L. F. Nicolas-Alonso and J. Gomez-Gil, "Brain Computer Interface, a Review," Sensors 2012, vol. 12, pp. 1211-1279, 2012.

[10] I. Kropotov and D. Kropotov, Quantitative EEG, Event-Related Potentials and Neurotherapy, Academic Press, 2009.

[11] R. Simpson (2005). "Smart wheelchairs: A literature review", Journal of Rehabilitation Research and Development, July/August, pp. 423-435, 2005.

[12] R. Braga, M. Petry, A. P. Moreira and L. P. Reis. "Concept and Design of the Intellwheels Platform for Developing Intelligent Wheelchairs", in LNEE/ Informatics in Control, Automation and Robotics, vol. 37, pp. 191-203, 2009.

[13] L. Project, "LURCH – the autonomous wheelchair," [Online]. Available: http://airwiki.ws.dei.polimi.it/index.php/LURCH_The_autonomous_wheelchair. [Accessed May 2011].

[14] J. Philips, J. Millan, G. Vanacker, E. Lew, F. Galán, P. Ferrez, H. Van Brussel and M. Nuttin, "Adaptive shared control of a brain-actuated simulated wheelchair," in 10th IEEE International Conference on Rehabilitation Robotics, Noordwijk, 2007.

[15] R. Blatt, S. Ceriani, B. D. Seno, G. Fontana, M. Matteucci and D. Migliore, "Brain control of a smart wheelchair," in 10th International Conference on Intelligent Autonomous Systems, Baden, 2008.

[16] B. Rebsamen, E. Burdet, C. Guan, H. Zhang, C. L. Teo, Q. Zeng, M. Ang and C. Laugier, "A Brain-Controlled Wheelchair Based on P300 and Path Guidance," in IEEE/RAS-EMBS International Conference , 2006.

[17] C. Mahl, G. Hayrettin, P. Danny, E. Marieke, S. Lasse, D. Matthieu and A. Alexandra, "Bacteriahunt: Evaluating multi-paradigm bci interaction," Journal on Multimodal User Interfaces, vol. 1, no. 4, pp. 11-25, 2010.

[18] R. Braga, M. Petry, L. P. Reis and A. P. Moreira, "IntellWheels: Modular development platform for intelligent wheelchairs", Journal of Rehabilitation Research & Development, 48, 9, pp. 1061-1076, 2011.

[19] R. Braga, M. Petry, A. P. Moreira and L. P. Reis, "Intellwheels: A Development Platform for Intelligent Wheelchairs for Disabled People". Proceeding of the 5th International Conference on Informatics in Control, Automation and Robotics. Vol I. Funchal, Madeira, Portugal, pp.115-121, 2008.

[20] B. M. Faria, S. Vasconcelos, L. P. Reis and N. Lau, "Evaluation of Distinct Input Methods of an Intelligent Wheelchair in Simulated and Real Environments: A Performance and Usability Study". Assistive Technology: The Official Journal of RESNA, DOI: 10.1080/10400435.2012.723297, 2012.

[21] Emotiv, "Emotiv," [Online]. Available: http://www.emotiv.com/. [Accessed May 2012].

[22] B. M. Faria, S. Vasconcelos, L. P. Reis and N. Lau, "A Methodology for Creating Intelligent Wheelchair Users' Profiles", ICAART 2012 - 4th International Conference and Artificial Intelligence, Algarve, pp. 171-179, 2012.

[23] Emotiv, Emotiv Software Development Kit - User Manual for Release 1.0.0.4, 2011.

[24] M. Hart, The 10-20 system, [Online]. Available: http://www.mariusthart.net/downloads/eeg_electrodes_10-20.svg. [Accessed 2012].

[25] B. Hjorth, "EEG analysis based on time domain properties," Electroencephalography and Clinical Neurophysiology, vol. 29, no. 3, pp. 306-310, 1970.

[26] A. Kaplan, J. Roschke, B. Darkhovsky and J. Fell, "Macrostructural EEG characterization based on non-parametric change point segmentation: application to sleep analysis," Journal of neuroscience methods, vol. 106, no. 1, p. 81–90, 2001.

[27] RapidMiner, "RapidMiner," 2012. [Online]. Available: http://rapid-i.com. [Accessed 2012].

[28] P. L. Rosenbaum, S. D. Walter, S. E. Hanna, R. J. Palisano, D. J. Russell, P. Raina, E. Wood, D. J. Bartlett, and B. E. Galuppi. "Prognosis for Gross Motor Function in Cerebral Palsy Creation of Motor Development Curves". JAMA: The Journal of the American Medical Association. vol. 288(11), Set 2002, pp. 1357-1363.