Brain Computer Interface based on Electroencephalographic Signal Processing

DAVID R. ACHANCCARAY, MARCO A. MEGGIOLARO

Abstract—**This work presents the development of a brain computer interface as an alternative communication channel to be used on the robotic field. It contemplates the implementation of an electroencephalograph, the computational methods and techniques necessary to accomplish this interface.**

An electroencephalograph is designed to acquire brain signals; basically conform by a triple amplification, a low-pass filter, high-pass filters and an analog-digital converter.

The processing of the digitized signal is composed by two stages, the preprocessing; in which, the electric noise is filtered and the artifacts are detected. The second stage is the processing strictly speaking; in which, the feature extraction that define to five kinds of chosen mental activities according to the brain specialization and brain computer interface references are computed; with these measures, a probabilistic neural network is trained to classify the kind of mental activity presented.

The training protocol is defined by three stages: the first stage is the training of a neural network to detect artifacts, a second stage is the training of a probabilistic neural network to classify the kind of mental activity, and the third stage is the mutual adaptation between the user and the system through the feedback of the classified mental activity and the updating of the neural network parameters.

Index Terms—**Brain Computer Interface; Electroencephalograph; Neural Networks; Wavelet Transform; Robotic.**

I. INTRODUCTION

The development of interfaces between humans and machines has been an expanding field in the last decades including several interfaces using voice, vision, haptics, electromyography (EMG) signals, electroencephalography (EEG) signals, and combinations between those as communication support [1].

Recent studies show the possibility to analyze brainwaves to derive information about the subjects' mental state that is then mapped into some external action such as selecting a letter from a virtual keyboard or moving a robotics device. A system that utilizes these brainwaves is called Brain Computer Interface (BCI) [2].

People who are partially or totally paralyzed (e.g., by amyotrophic lateral sclerosis (ALS) or brainstem stroke) or have other severe motor disabilities, they can find a BCI as an alternative communication and control channel that does not depend on the brain's normal output pathway of peripheral nerves and muscles. A BCI makes it possible that these persons enhance their life quality [3].

Non-invasive BCIs are based on the analysis of EEG phenomena associated with various aspects of brain function [1]. Thus, Birbaumer [4] measure slow cortical potentials (SCP) over the vertex (top of the scalp). SCP are shifts in the depolarization level of the upper cortical dendrites and indicate the overall preparatory excitation level of a cortical network. Other groups look at local variations of the EEG rhythms. The most used of such rhythms are related to the imagination of movements and are recorded from the central region of the scalp overlying the sensorimotor cortex. In this respect, there are two main paradigms. Pfurtscheller's team works with event-related desynchronization (ERD) computed at fixed time intervals after the subject is commanded to imagine specific movements of the limbs [5]-[6]. Alternatively, Wolpaw [7] and coworkers analyze continuous changes in the amplitudes of the mu (8-12 Hz) or beta (13-28 Hz) rhythms.

Finally, in addition to motor-related rhythms, Anderson [8] and Millán [9] analyze continuous variations of EEG rhythms, but not only over the sensorimotor cortex and in specific frequency bands. The reason is that a number of neurocognitive studies have found that different mental activities (such as imagination of movements, arithmetic operations, or language) activate local cortical areas at different extents. The insights gathered from these studies guide the placement of electrodes to get more relevant signals for the different tasks to be recognized. In this latter case, rather than looking for predefined EEG phenomena as in the previous paradigms, the approach aims at discovering EEG patterns embedded in the continuous EEG signal associated with different mental states.

These different BCI systems are used to operate a number of brain-actuated applications that augment people's communication capabilities, provide new forms of education and entertainment, and also enable the operation of physical devices [2]. The subject controls active devices by carrying out mental activities, which are associated with actions depending on the BCI application [1].

BCI applications include control of the elements in a computer-rendered environment (e.g. cursor positioning [3], [1]), visit of a virtual apartment [10]-[11]), spelling programs (e.g. virtual keyboard [12]), and command of an external device (e.g. robot [13], prosthesis [14]).

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Recent applications into the robotic field are the control of a wheelchair [15] and the control of the robot Khepera [16]; these applications could be the basis for the implementation of an external skeleton to return the total mobility of a quadriplegic person.

In this work, the hardware and the software for a BCI system is developed. The hardware for the acquisition of EEG signals is implemented in two stages; an amplification stage and an analogical-digital conversion (ADC) stage. The software of the BCI system is developed in C# language at Visual Studio 2005 environment linking developed functions in the MATLAB program for the EEG signal processing and the recognition of mental activities.

II. Implementation of an Electroencephalograph

An electroencephalograph is a device that records the brain activity through electrodes placed on the scalp. The acquisition encompasses different kinds of waves that depend on the position of the electrodes.

Electroencephalography has an invaluable support to the diagnostic of diseases of the central nervous system (CNS) that compromise the structure of the neurons. One of the pathologies where the electroencephalography is most useful is in the study of epilepsy, featuring unusual excitability of the neurons [17].

The block diagram of the implementation of the electroencephalograph is presented in Fig. 1.

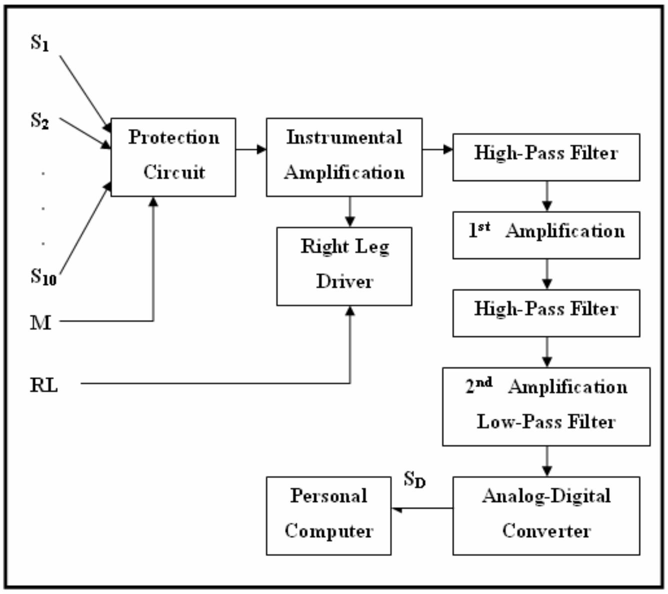

Fig. 1. Block diagram of the implementation of the electroencephalograph.

A. *Protection Circuit*

The protection circuit is connected to external electrodes. It is the first stop for the EEG signal entering the amplifier box. This initial stage suppresses RF signals that enter the system through the electrode cables and limits the input voltage [18].

B. *Instrumental Amplification*

An instrumental amplifier controls the differential input and determine the common-mode rejection ratio (CMRR). It will remove noise of the input signals [18].

C. *Right-Leg Driver*

The Right Leg Driver is used to raise the common-mode rejection ratio of the instrumentation amplifier. With this higher signal-to-noise ratio (SNR), the differential signal obtained is ensured to possess only relevant information and a minimum of interference currents or irrelevant data [18].

D. *Amplification*

The amplification circuit is achieved in two stages: two high-pass first order filters are included between the amplifications, with a cutoff frequency of 0.16 Hz to remove DC-voltage offsets. The second amplification contains a low-pass second order Butterworth filter, with a cutoff frequency of 100 Hz. This bandwidth is due to the range of frequencies of the brainwaves, which is from 0 to 100 Hz.

E. *Analog-Digital Converter*

The analog-digital conversion is the means by which the signals are digitalized for the subsequent processing. The digitalization is carried out through the data acquisition system CompactDAQ from National Instruments; this system covers the components NI 9205 analog input module and the NI cDAQ-9172 chassis [19].

The components of the electroencephalograph implemented are shown in Fig. 2.

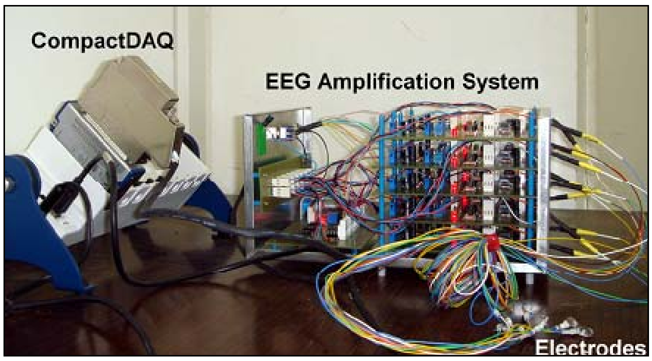

Fig. 2. Components of the electroencephalograph implemented.

III. Preprocessing

The extraction of information from EEG data is hindered by external noise and subject-generated artifacts. Most sources of external noise can be avoided by appropriately controlling the environment in which the measurement takes place. Thus, power line noise can be easily filtered since it occupies a narrow frequency band that is located beyond the EEG band [1].

Subject-generated artifacts (eye movements, eye blinks and muscular activity) can produce voltage changes of much higher amplitude than the endogenous brain activity. Even when artifacts are not correlated with tasks, they make it difficult to extract useful information from the data. In this situation the data is discarded and the subject is notified by a special action executed by the BCI. If the data containing artifacts were not discarded they could lead to misleading conclusions about the controlling performance of a subject [1].

The preprocessing removes external noise from EEG trials and detects the presence of artifacts. The power line noise is considered as external noise; eye blinks and eye movements are defined as ocular artifacts, while muscular activity is referred to as muscular artifact.

The block diagram of the preprocessing is presented in Fig. 3.

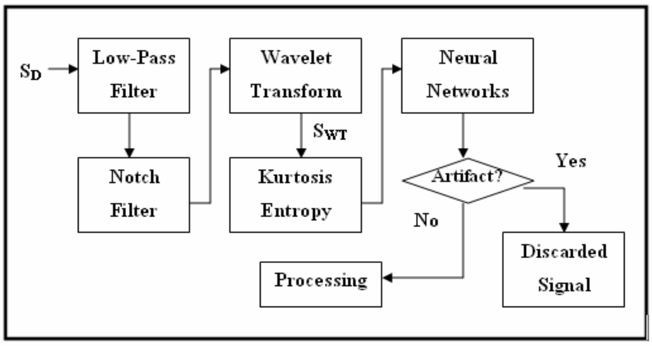

Fig. 3. Block diagram of the preprocessing.

A. Electrical noise

A Butterworth fourth order digital filter, with passband edge of 30 Hz and stopband edge of 100 Hz [20]; and notch filter centered in 60 Hz [21]-[22], guarantee the elimination of the electrical noise.

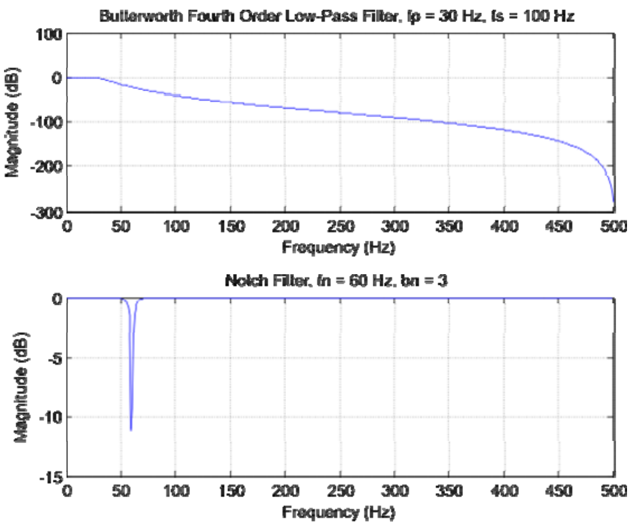

Fig. 4. Frequency response of the Butteworth and notch filters.

B. Artifact Detection

The presence of eye movements, eye blinks and muscular artifacts in EEG signals can be easily detected from simple observation. As a matter of fact, each type of artifact has characteristics in time and frequency that make it distinguishable from regular EEG [1].

Ocular artifacts have large amplitudes; their spectral content is mainly concentrated in the theta band and they are more prominent at frontal pole electrodes, i.e. Fp1 and Fp2 (from the International System 10-20), see Fig. 5.

Muscular artifacts have amplitudes in the order of that of regular EEG, but their spectral content is concentrated in the beta band. These artifacts are more noticeable in central temporal and parietal electrodes, i.e. electrodes T3, T4, T5, P3, P4 and T6 [23], see Fig 5.

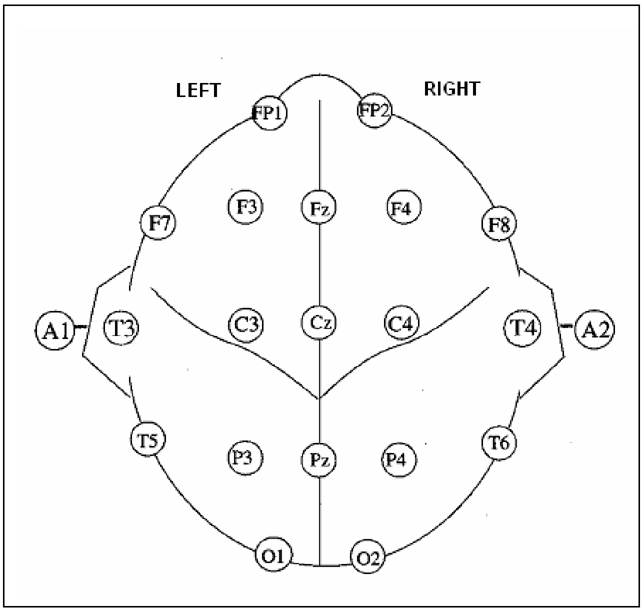

Fig. 5. Electrodes positions from the International System 10-20.

Artifacts can be considered as singular events in the time-frequency plane that appear randomly in EEG signals. To detect the presence of artifacts in an EEG trial, the EEG signals are acquired in segments of two seconds; after the application of the filters, the digital wavelet transform (DWT) is applied to decompose the signal frequency band to extract the EEG bands.

1) Wavelet Analysis

The EEG signal is decomposed through the DWT until achieving the frequency ranges of the brainwaves; the DWT is applied in seven levels, according to Fig. 6, in order to approximately form the four principal frequency ranges of the brainwaves [24]:

- Delta Band [0 – 4 Hz]: (n).
- Theta Band [4 – 8 Hz]: (o).
- Alpha Band [8 – 13 Hz]: (p).
- Beta Band [13 – 30 Hz]: (q) and (k).

The sample rate (F_S) is 1000 Hz; then, the decomposition of frequency ranges begins in the range of 0 to 500 Hz.

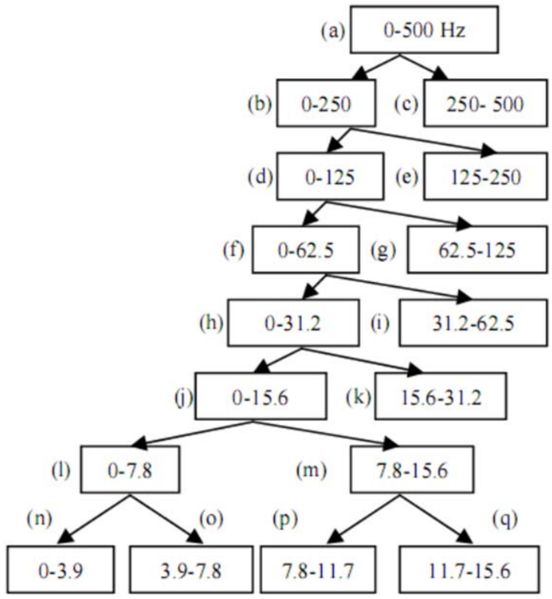

Fig. 6. DWT decomposition of the frequency range.

The beta and theta bands are processed to obtain their respective wavelet coefficients using the electrodes Fp1, Fp2, P3 and P4.

2) High-Order Statistics

Wavelet coefficients with artifactual activity are supposed to be "odd" with respect to other ones when an unexpected event occurs and involves its frequency range, or when it carries information about a noisy background activity. Thus, a measure of randomness might help to detect them. EEG artifacts such as eye blinks and heartbeat are typically characterized by a peaky distribution and could be detected by a measure of peakyness [25].

The parameters that can measure the randomness and the peakyness are entropy and kurtosis, respectively [26].

Given a scalar random variable x, kurtosis (k) has the following expression:

$$k = m_4 - 3m_2^{\;2} \tag{1}$$

$$m_n = E\{(x - m_1)^n\} \tag{2}$$

where m_n is the n-order central moment of the variable and m_1 is its mean.

The definition of the Renyi's entropy is shown in Eq. (3), where α (α ≥ 1) is the order of the entropy. Equations (4-5) come from the application of the kernel estimators. The order of the entropy is set at 2, in order to equally emphasize the sub-Gaussian and the super-Gaussian components.

$$H_{R_\alpha}(X) = \frac{1}{1-\alpha}\log\sum_i P^\alpha(X = a_i) \tag{3}$$

$$H_{R_\alpha}(x) = \frac{1}{1-\alpha}\log\int_{-\infty}^{\infty}\rho_X{}^\alpha(x)dx \tag{4}$$

$$H_{R_\alpha}(X) = \frac{1}{1-\alpha}\log\{\frac{1}{N^\alpha}\sum_j[\sum_i k_\sigma(x_j - x_i)^{\alpha-1}]\} \tag{5}$$

Before computing the entropy and the kurtosis of the wavelet coefficients, they are normalized with zero-mean and unit-variance. After computing the statistic data, it is observed that a simple threshold is not enough to discriminate the occurrence of artifacts [27].

3) Neural Networks

The detection system is tested with two kinds of neural networks as classifiers: multilayer perceptron (MLP) and probabilistic neural network (PNN). The detection system consists of two neural networks, of the same class, joined through a logic operation OR, see Fig. 7.

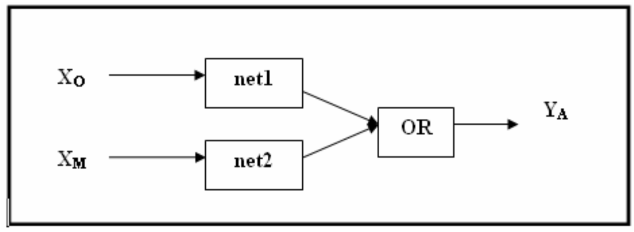

Fig. 7. Neural network block to detect artifacts.

The MLP has the ability to be an universal approximator, it learns and generalizes with smaller training set requirements. It has a fast operation, ease of implementation and therefore it is the most commonly used neural network architecture. It has been adapted to discriminate between the occurrence and the non-occurrence of artifacts [24].

The second kind of classifier is a PNN scheme. The PNN network is rapidly trained; it is usually faster than the MLP, while exhibiting none of its training pathologies such as paralysis or local minima problems [24].

Detection of ocular artifacts is done using the wavelet coefficient kurtosis of the four electrodes (Fp1, Fp2, P3 and P4) in the frequency ranges beta (o) and theta (k), see Fig. 6, where X_O is a feature vector of occurrence of an ocular artifact, see Fig. 7.

Detection of muscular artifacts is done using the wavelet coefficient entropy and kurtosis of three electrodes (Fp1, Fp2 and P4) in the frequency range theta (k), see Fig. 5, where X_M is a feature vector of occurrence of a muscular ocular artifact, see Fig. 7.

An experiment is developed to validate the procedure, considering 300 trials: 100 trials without artifacts, 100 trials with ocular artifacts, and 100 trials with muscular artifacts. The training of the neural networks is described next.

Neural network 1 (net1) is trained using 100 trials without artifacts, and 100 trials with ocular artifacts, taking 80% of the trials for the training data and 20% for the validation data.

Neural network 2 (net2) is trained in the same way, however using muscular instead of ocular artifacts.

Cross-validation is applied to determine the neural network with the better performance in the classification, the 20% of the trials for the validation data of the networks is taken through all the samples, resulting in five possible neural networks [28].

The union of the neural networks (netf) made through a logic operation OR as mentioned before, is then tested for the total of the trials. The results of the tests of the neural networks are shown in Tables I and II.

TABLE I
TEST OF THE MLP NEURAL NETWORKS.

	C	I	Total	Hit Rate (%)
net1	35	5	40	87.5
net2	27	13	40	67.5
netf	283	17	300	94.3

C: Correct. I: Incorrect.

TABLE II
TEST OF THE PROBABILISTIC NEURAL NETWORK.

	C	I	Total	Hit Rate (%)
net1	24	16	40	60.0
net2	27	13	40	67.5
netf	284	16	300	94.6

C: Correct. I: Incorrect.

Tables III and IV show the confusion matrices of the detection system using MLP and PNN, respectively.

TABLE III
CONFUSION MATRIX OF THE CLASSIFICATION WITH MLP NEURAL NETWORKS.

	S	SA
S	87	13
SA	4	196

S: Signal without artifact. SA: Signal with artifact.

TABLE Iv
CONFUSION MATRIX OF THE CLASSIFICATION WITH MLP NEURAL NETWORKS.

	S	SA
S	88	12
SA	4	196

S: Signal without artifact. SA: Signal with artifact.

IV. PROCESSING

The BCI developed in this work is based in operant conditioning. The mental activities defined specifically are the motor imagery of the forefinger movement of the right hand to the right and to the left side, imagination of the 3D rotation of a cube, arithmetic operation of subtraction by a constant number and the mental state of relax.

After the application of the wavelet transform, the wavelet coefficients contain useful information in the time and frequency domain. The next step is the feature extraction, which consists on computing a few measurements from which it is possible to determine the different mental activity kinds.

In this case, the chosen measurement is the mean of the wavelet coefficients in the principal frequency bands of the brainwaves; where X_μ is the feature vector of the means of the wavelet coefficients.

Pattern recognition consists in determining an algorithm to classify the signal's features according to the corresponding mental task. A probabilistic neural network is used as classifier, obtaining a high hit rate; the classifier must be able to recognize five different mental activities.

To train the neural network, 500 trials are taken where the user is asked to carry out 100 trials of the chosen mental activities: motor imagery of the forefinger movement to the right side (RM), motor imagery of the forefinger movement to the left side (LM), 3D rotation of a cube (CR), arithmetic operation of subtraction (AS), and the mental state of relax (RX).

After computing the mean of the wavelet coefficients, the dimension of the feature vector is 50; using the knowledge of the specialization of the brain activity and the position of the electrodes it is possible to discard the electrodes Fp1, Fp2, P3 and P4, achieving a reduction of the dimensionality to 30. Then, the brain activity principal concentration is observed in the delta band [0 – 4 Hz], reducing the dimensionality to 6.

Validation of the classifier allows discarding the electrodes C4 and Pz, then the final dimension of the feature vector is 4. The reduction of the dimensionality eases the training and application of the neural network. Therefore, the processing time is reduced too, which is an important requirement for applications in real time (see Fig. 8, where MA is the recognized mental activity).

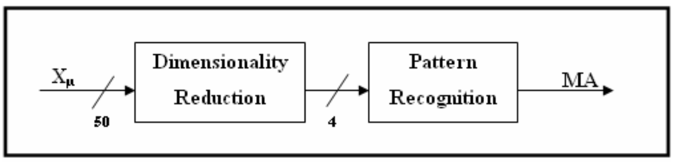

Fig. 8. Pattern recognition of the five mental activities.

The trials with their reduced feature vector are divided in the following way: 80% of the trials are taken for the training data and 20% for the validation data. Cross-validation is applied in the same way that in the artifact detection, to determine the neural network with better performance in the classification [28].

Table V shows the confusion matrix from the classification in the stage of validation of the neural network. The obtained hit rate is 83%.

TABLE V
CONFUSION MATRIX OF THE CLASSIFICATION OF THE MENTAL ACTIVITIES WITH A PNN NEURAL NETWORK.

	RM	LM	CR	AS	RX
RM	16	4	0	0	0
LM	0	15	5	0	0
CR	1	5	14	0	0
AS	1	1	0	18	0
RX	0	0	0	0	20

V. APPLICATION

The stages of training and application of the BCI must be automatic processes; the development of a graphic interface that can link all the subsystems in different programming environments, and interact with the available hardware is necessary.

The graphic interface is developed in the programming environment Visual C#, adding libraries to run routines in Matlab to control data acquisition through the "CompactDAQ" and to send commands for the mobile robot by the radiofrequency (RF) interface. This interface offers to the user a friendly environment to develop the skill of controlling his/her brain activity while the system can adapt with him/her.

The validation of the BCI is made through of an application which consists on the activation of the movements of a mobile robot associating the mental activities to commands that can be sent to the robot by the radiofrequency interface. This application is tested with five users, evaluating the performance of the BCI with different measurements that explain the accuracy and speed of the integrated system.

A. Training Protocol

The first stage consists on the artifact detection through the training of two neural networks, which detect the occurrence of ocular and muscular artifacts.

The second stage consists on the mental activity recognition through the training of a PNN, which is achieved classifying the five kinds of mental activities.

The third stage consists on the mutual adaptation between the system and the user, providing to the user visual feedback (biofeedback). In such feedback, the mental activity to be developed is shown randomly on the screen. If the classifier point out a different mental activity; then, the acquisition is discarded.

This procedure is repeated so much as to complete 10 trials of each kind of mental activity. The trials are added to the PNN neural network, where the obtained data in the section 4.4 is used to validate this procedure. 10% of the trials are taken for the stage of the mutual adaptation, while another 10% of the trials are taken for validation data.

The hit rate of the network of the second stage is 82%, while that the hit rate of the network of the third stage is 92%.

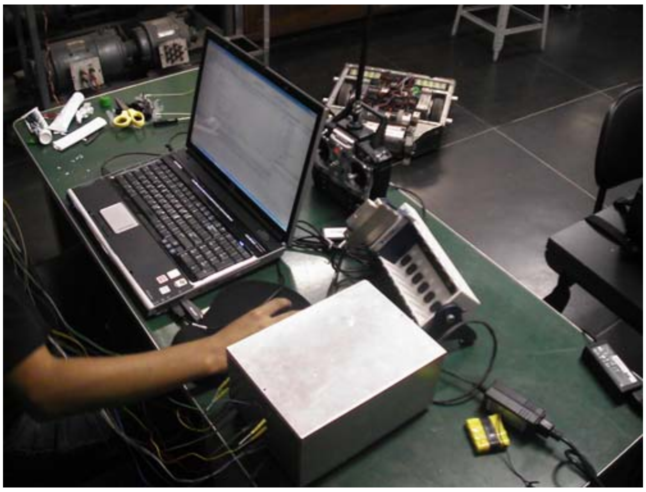

Fig. 9. Training protocol applied to a user

B. Mobile Robot

To validate the proposed methodology, the developed BCI is applied to a 120 pound mobile robot. The chosen mobile robot, named *"Touro"* (see Fig. 5.5), was already available at PUC-Rio's Robotic Laboratory, setup to respond to RF commands, therefore no further development was necessary. In addition, this system is analogous to a powered wheelchair, one of the possible applications of the BCI: it is driven by only two active wheels (see Fig. 10) using "tank steering", and it has enough torque to carry an adult.

The BCI commands are translated to five different commands: turn right, turn left, move forward, move backward, and stop.

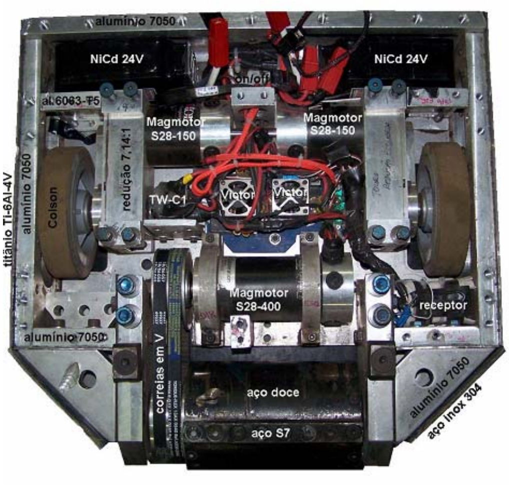

Fig. 10. Differential traction configuration of the mobile robot "*Touro*".

The training protocol take approximately two hours, the graphical interface was programmed to accomplish the three stages of the training automatically and sequentially. The application to activate the robot is contained in the graphical interface, each processing of a command take approximately thirty seconds; therefore, the rate is two commands/minute. The hit rate obtained of the application is 60 %.

VI. CONCLUSION

An asynchronous operant conditioning BCI was developed, which operates with five mental activities in the activation framework of a mobile robot, the BCI sends commands each thirty seconds.

An efficient algorithm to detect ocular and muscular artifacts was developed based on the training and composition of two neural networks. The parameters of this artifact detection system were set during a first training stage.

It was found that the selected features to train the neural networks in the artifact detection stage and the recognition stage represent suitably the behavior of the EEG signals in the frequency-time domain in each band of the EEG analysis.

The BCI can evolve to a Brain Machine Interface (BMI), which is implemented in an embedded system. The BMI will offer portability and improved user friendliness.

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