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Extraction of features of kinesthetic activities in the upper limb from EEG recordings based on sub-band analysis with wavelet transform for the control of robotic assistance systems

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***Abstract*—In the literature, findings of movement and force control of non-intrusive robotic assistance systems have been reported, based on the processing of electroencephalogram (EEG) recordings and the conditioning of the control strategy. However, the collection of signals in the cerebral cortex may not represent the set point defined in the cerebellum, particularly in post-cerebral stroke patients. The present study reports a new proposal inspired by human intention of a gross motor action assisted by a robotic platform. For this, a BCI (Brain-Computer Interface) system is used, based on the instrumentation of EEG signals, specifically from the cerebral cortex, and its digital processing using wavelet multiresolution analysis for the detection of features associated with real and imagined kinesthetic tasks, such as: upper limb movement and manipulation of objects. The main result is associated with the position control of a direct current motor and the motion control of a 2 DOF manipulator robot, with a high performance adaptive wavenet PID control for stabilization of non-linear MIMO (Multiple Inputs Multiple Outputs) systems.**

***Index Terms*—Human-Robot Interaction, Brain Computer-Interface, Multiresolution Analysis, PID Wavenet Control**

I. Introduction

A BCI system acquires and analyzes the EEG signal (electroencephalogram recordings) in order to provide a direct communication and control system between the brain and the computer. Some research has focused on the control of motorized wheelchairs that allow moving people with a motor disability, in particular with spinal cord injury. The control is achieved by means of an electronic module that has the ability to direct the chair by tilting the head detected by an accelerometer [1]. The independence of people with severe motor disabilities represents an important step through the use of BCI systems, taking advantage of the benefits of the internet of things, to perform complex tasks without a large workload [2]. People with motor disabilities cannot access these simple interfaces due to their inability to direct the movement of their body to perform certain tasks such as pressing a key or button on the device, for these people, the use of a Eye Gesture Communication (EGCS) is of great importance, as it gives them the opportunity to convey their needs to other people through the movement of their eyes [3]. With the increase in cases and complexity of movement disorders, new rehabilitation paradigms have been proposed addressing the plasticity of the brain to recover motor function, proposals for hybrid BCI systems with Virtual Reality (VR) systems that combine training that are custom made engine with virtual environment [4].

The BCI offers solutions for those with a neuromuscular disorder. In fact, it provides a new communication channel to control external devices. The precision of the classification of parameters is essential for the performance of the systems, the selection of the specific frequency bands of each cortical area also provides an important improvement, for this, methods such as Welch's are used for the estimation of Spectral Density of Power (PSD) has been used for feature extraction followed by two different classification methods Linear Discriminant Analysis (LDA) and Quadratic Discriminant Analysis (QDA) in order to achieve good performance [5].The LDA has been widely adopted to classify Event Related Potential (ERP) in BCI systems. Good ERP-based BCI classification performance generally requires sufficient data records for effective LDA classifier training and therefore lengthy system calibration time which, however, can reduce the viability of the system and cause users resist the BCI system, with the use of Spatio-Temporal Discriminant Analysis (STDA) it is sought to maximize the discriminant information between the target and non-target classes by searching for two projection matrices of spatial and temporal dimensions in collaboration, which which effectively reduces the dimensionality of the feature in discriminant analysis, and thus significantly decreases the

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number of training samples required, in the era of new argumentative technology, EEG signals are widely employed in BCI engagement [6], [7]. For people with lower extremity paralysis, spinal cord injury and other diseases, the use of the lower extremity rehabilitation robot is to obtain trajectory training, which is a good means of recovery, the goal of passive control is to help the pre-adaptive training of the patient; which refers to the training of the patient's legs, which can be seen as part of the exoskeleton [8]. The control of the rehabilitation systems is fundamental to improve the rehabilitation training that is why strategies are proposed for the force adaptation control of the rehabilitation robot and the adaptive slip mode control method based on in the RBF neural network. However, the computational cost of closing the control loop with the BCI system continues to be high, so the implementation of wavelet analysis techniques favors the performance of the systems [9], [10].

This paper presents the characterization of the brain signals of motor activities that help to design and implement assistance systems for people with motor disabilities. The purpose is to contribute to the development of new technologies that help improve the quality of life of people who present some type of motor disability, the importance of this work lies in the implementation of wavelet multiresolution analysis in the processing of brain signals to characterize the frequency bands and find patterns of movement and force. The main hypothesis is the extraction of characteristics of the brain signals generated by movement and strength tasks of the upper limb, so that people with motor difficulties have an alternative to communicate with the outside world. The main objective of the work is to implement a communication scheme for the control of a robotic device through wavelet multiresolution decomposition, this result brings us closer to the development of more complex robotic systems controlled from the imagination of movements, the control scheme is favored by the implementation of a wavelet multiresolution control and thus collaborate in the communication of the human brain with external devices.

II. EXPERIMENTAL METHODS AND MATERIALS

A. Subjects

The signals were acquired from 10 healthy subjects between 25 and 35 years of age, all with postgraduate studies, the sample consisted of 4 female and 6 male, all right-handed. The acquisition of signals was carried out under a controlled environment with the consent of all the participants, they were made aware that the placement of the sensors in the cerebral cortex was a non-invasive method so it did not cause any damage or physical alteration. The subjects have no prior knowledge of the training or the task of movement, execution and force imagination, these instructions were explained verbally and individually to each subject before starting the recording of the brain signals.

B. Experimental task

The task was based on the Motor Imagination paradigm, the subject sat on a chair in front of a table and a computer. The registration of brain signals was given in a period of time of two minutes with the eyes open, for the first activity recorded which was the movement of the right hand, the instruction was given that when the computer emitted a sound the subject had to make the movement of hand upwards and downwards, for the second task that is of force performed the same instructions were given, that when the tone is heard in the computer force will be carried out by pressing a ball with the right hand and finally for the imagination of force, the subjects were asked to do it with their eyes closed and to be guided by the tone of the computer, when listening to the tone they would imagine the force with which they squeezed the ball in experiment two. The tests were repeated 5 times to have comparison signals and to select a pattern of behavior.

C. Signal acquisition

The brain signals shown in Figure 1 were recorded using the Emotiv EPOC 16-channel helmet. The 16 electrodes were placed on the scalp of the subjects according to the international 10-20 system. This wireless device has 14 electrodes plus two reference electrodes as shown in Figure 2,it has the advantage of ease of use and development. The time it takes to prepare it is also considerably lower than a conventional EEG device.

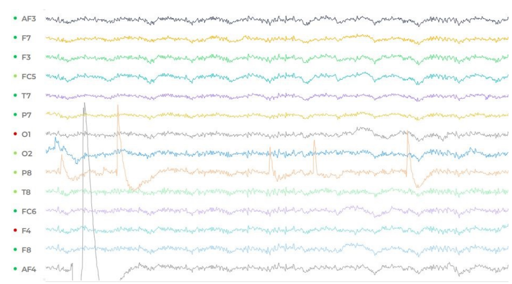

Fig. 1. Brain signal related to a motor activity captured by the Emotiv EPOC device.

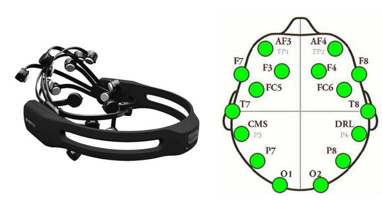

Fig. 2. The Emotiv EPOC device has 14 electrodes and two reference electrodes placed on the scalp according to the international 10-20 system.

D. Signal pre-processing

The objective of this stage is to attenuate signals of high frequencies $60Hz$, that are coming from external sources such as electricity power and to make the signals of zero mean to have normalized signals. The algorithm used in this article is a differentiator with a filter a $62.5Hz$ [11]

$$Y[n] = f[n] - f[n-4], 4 < n < N \tag{1}$$

where, N is the number of samples delivered by the Emotiv Epoc.

E. Signal analysis

The procedure to obtain the resolution of the EEG signals begins by passing the signal (sequence) through a digital low-pass filter with impulse response $\overline{h[k]}$, this filtering process consists of mathematically performing the convolution of the sequence with the impulse response of the filter, which is defined as:

$$f[n] * \overline{h[n]} = \sum_{k} f[k] \cdot \overline{h[n-k]} \tag{2}$$

A low pass filter attenuates all frequencies that are above half the highest frequency of the signal, for example, if the signal has a maximum component of $45Hz$,this filter attenuates all frequencies above $22.5Hz$

Note that the low-pass filtering attenuates the high-frequency information, but leaves the scale unchanged, since only the sub-sampling process alters it. On the other hand, since the resolution is related to the amount of information in the signal, it is altered by the filtering operations. Low pass filtering attenuates half the frequencies, which can be interpreted as a loss of half the information. However, the sub-sampling process after filtering does not affect the resolution, since it attenuates half of the spectral components, half the number of samples become redundant as well, thus half the number of samples can be removed without no loss of information.

The decomposition of the signal into different frequency bands is obtained by successive low-pass and high-pass filtering, therefore the original signal $f[n]$ is passed through a high-pass filter $\overline{g[k]}$ and a low-pass filter $\overline{h[k]}$; After this filtering, half of the samples can be eliminated, for which one out of every two samples is eliminated (subsampling by 2). In this way, the first level of decomposition has been constituted, which mathematically can be expressed as:

$$d_i[n] = \sum_{k=0}^{\kappa-1} \overline{g[k]} c_{i-1,k}[2n-k] \tag{3}$$

$$c_i[n] = \sum_{k=0}^{\kappa-1} \overline{h[k]} c_{i-1,k}[2n-k] \tag{4}$$

where $d_i[n]$ y $c_i[n]$ are the outputs of the high pass and low pass filters, respectively, after subsampling by 2.

Figure 3 shows the procedure, where $f[n]$ is the original signal to be decomposed and $\overline{h[k]}$ and $\overline{g[k]}$ son are the low pass and high pass filters respectively.

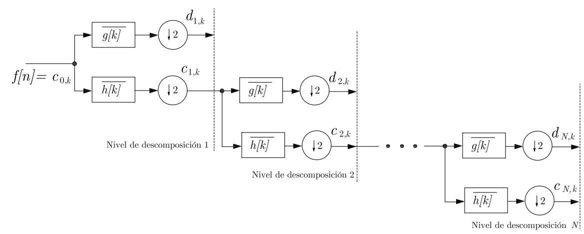

Fig. 3. Decomposition analysis of the $f[n]$ signal of brain activity.

In this particular case of study, a signal of n samples and a frequency in the range of $[0, 45Hz]$. In the first level of decomposition, the $f[n]$ signal is passed through the high pass filters $\overline{g[k]}$ and low pass filters $\overline{h[k]}$, continuing to be sub-sampled by two

The output of the high pass filter will have $n/2$ samples with which the resolution in time has been divided in half, but the frequency now covers the band between $[22.5, 45Hz]$ that is, the resolution in frequency has been doubled. These $n/2$ samples constitute the first level of the DWT coefficients (Discrete Wavelet Transform).

The output of the low-pass filter will also have $n/2$ samples, but with a frequency that covers the range between $[0, 22.5Hz]$, his output signal continues to decompose, passing it again through high-pass and low-pass filters, so on until obtaining the Desired resolution level, for this case study the level of decomposition is 5, in Figure 4, the decomposition of the EEG signals related to the movement of the hand, the force performed and the imagined is shown of the upper limb respectively, where it can be seen that through the sub-band decomposition process we can find the frequencies of brain activity related to the tasks performed.

Frequencies that are more dominant in the original signal

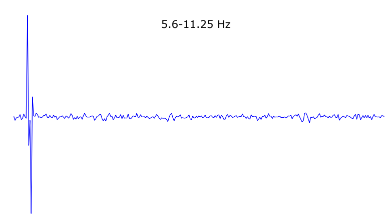

Fig. 4. Decomposition of the frontal region sensor signal AF4 related to force performed from upper limb.

will appear as high amplitudes in the region of the DWT that includes those frequencies as the Figure shows 5 [12]. The difference between FT and DWT is that with DWT the location of these frequencies is not lost in time. However, the location in time will have a resolution that will depend on the level at which it appears, in this way if the main information contained in the signal is in high frequencies, as is often the case, then the location in time will be more accurate, since they will be characterized by a greater number of samples.

On the other hand, if the main information is at very low frequencies then its location in time cannot be very precise, since there will be very few samples to characterize the signal at these frequencies.

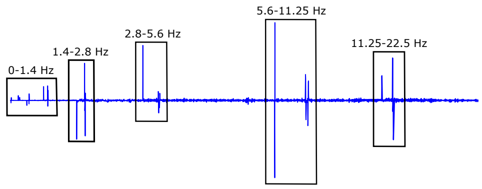

Fig. 5. Wavelet transform of force signal with upper right hand.

F. Multi-resolution control

Figure 6 shows a classic control scheme, where the controller used is a PID. If a mathematical model of the plant can be obtained, it is possible to apply various design techniques in order to determine the parameters of the controller that meets the transient and steady state specifications of the closed-loop system [13]. A classical control system basically

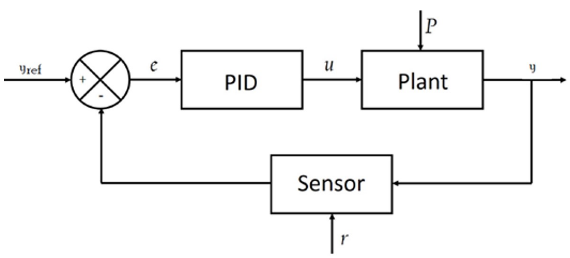

Fig. 6. PID control scheme with external uncertainty and noise in perception.

consists of three important parts which are: the plant, which can be affected by external disturbances P, the sensor block, and finally the control that makes the plant perform in a predetermined way so that output y and approach y_{ref}.
In general, a PID control takes as input the error signal $e(t)$ nd generates a control signal $u(t)$ [13],

$$u(t) = k_P e(t) + k_I \int_0^t e(\tau)d\tau + k_D \dot{e}(t) \tag{5}$$

where k_p, k_I y k_D sare the PID gains, and $e(t)$ is the error signal defined as,

$$e(t) = y_{ref}(t) - y(t) \tag{6}$$

The discrete form of the is [14]:

$$u(k) = u(k-1) + k_p[e(k) - e(k-1)] + \\ k_I e(k) + k_D[e(k) - 2e(k-1) + e(k-2)], \tag{7}$$

Taking the gains k_P, k_I and k_D as adjustable parameters, then (7) can be described as

$$u(k) = u(k-1) + \sum_{i=0}^{2} k_i e(k-i), \tag{8}$$

o equivalente

$$\triangle u(k) = \sum_{i=0}^{2} k_i e(k-i), \tag{9}$$

where $k_0 = k_P + k_I + k_D$, $k_1 = -k_P - 2k_D$ y $k_2 = k_D$.
However, if the plant is very complex that it is not easy to obtain its mathematical model, neither is an analytical method for the design of a PID controller possible. In this case, one must resort to experimental procedures for tuning the PID controllers or resort to another type of control such as the CPM (Proportional Multi-resolution Control).
From (9), it can be seen that the control law of a classic PID is a linear decomposition of the error that consists of three terms, this makes the difference between the classic PID and the CPM (Proportional Multiresolution Control) [14],where here the decomposition number can be infinite, the CPM method decomposes the error signal into high, medium and low frequencies, making use of the multiresolution analysis of the tracking error signal $e(t)$.
Each of these components of the multiresolution synthesis output are scaled with their respective gains and finally added to generate the corresponding control signal $u(t)$ as shown below,

$$u(t) = K_H e_H + K_{M_1} e_{M_1} + \\ K_{M_2} e_{M_2} + ... + K_{M_{N-1}} e_{M_{N-1}} + k_L e_L \tag{10}$$

$$u(k) = KE \tag{11}$$

where

$$K = [K_H \; K_{M_1} \; ... \; K_{M_{N-1}} \; K_L] \tag{12}$$

$$E = [e_H \; e_{M_1} \; ... \; e_{M_{N-1}} \; e_L]^T \tag{13}$$

Where N is the CPM decomposition level, the CPM parameters depend on the decomposition levels of the plant error signal, it can have two or more parameters depending of N [14].

III. RESULTS

A. Control system for a single input-single output scheme

The signs EEG are highly non-stationary and not-nonlinear. Therefore, the algorithms used in the processing must be considered to characterize the signal analyzed in this article. EEG is decomposed by multiresolution analysis based on wavelets shown in Figure 3. With the help of this algorithm we can separate the frequency bands related to kinesthetic activities as shown in Figure 4 .
For the implementation of the BCI, the model of a DC motor is presented, it is assumed that the wavelet to be used is Daubechies 4 of order 2. For the multiresolution analysis of the error signal $e(t)$, the decomposition level is $N = 3$. The filter coefficients are Daubechies [14].
A CPM is applied to control the position of a DC motor. The transfer function that models the motor is given by:

$$G(s) = \frac{b}{s(Js + c)} \tag{14}$$

where $b = 22Nm/volts$ represents the torque constant. The friction coefficient is given by $c = 4Kgm^2/segrad$ and the total inertia of the motor $J = 1Kgm^2/rad$ [14].
The way to connect the BCI system with the control scheme is by means of a function that defines a threshold for the detection of the BCI command, in Figure 1, the sensors used for the procedure are shown. The detection BCI command can obtain the reference signal (y_{ref}) for the control scheme.
In Figure 4 shows signal c_1 with the second level of decomposition, that corresponds to the *Alpha* and *low beta* band that contains frequencies that correspond to the imagination and execution movements of the body extremities. Being the execution of movements the case of this study, the coefficients are in the frequencies of $[5.6 - 11.25Hz]$ that belong to the component c_2 correspond to activities [15].
Knowing the band where the activity of interest is recorded, a threshold of the form is calculated [11]

$$U = 0.3 \cdot max(c_2) \tag{15}$$

where U is between $[0.04, 0.08]$ the obtaining of the interval is calculated experimentally, it is worth mentioning that the parameters of U are calculated online, the reference for the control scheme is of the form

$$y_{ref} = \Omega \cdot U \tag{16}$$

where $\Omega = 62.5$ is proposed so that the maximum value of y_{ref} corresponds to two turns of the motor, this result is used for the design of a CPM control law.

For the design of the CPM control, the gains from [14], are taken, shown in table I,

K_H	K_{M1}	K_{M2}	K_L
2	4	10	0

TABLE I
CPM GAINS

Figure 7 shows the motor output position represented in rad.

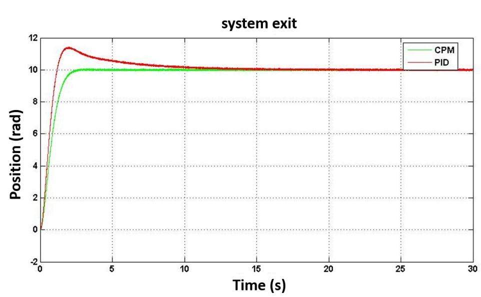

Fig. 7. Motor position at 10 rad equivalent to 1.6 turns applying a CPM compared to a PID control.

In order to have a comparative study, a classic PID control is implemented for the same system and under the same operating condition.

B. *Control system for a multiple input-multiple output scheme*

Another implementation of the BCI is considered a robot with two degrees of freedom, the scheme shown in Figure 8 corresponds to a multi-resolution controller, proposed for the control of the system [14]; in this case, the control proposed allow adaptive compensation of the output dynamics of a robot manipulator with the human in the loop (as a perator in haptic guidance scheme). The equation that represents the robot, is

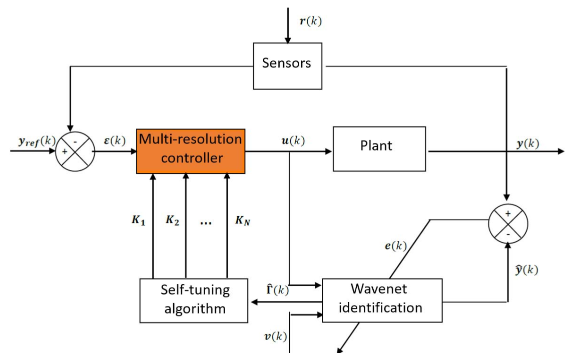

Fig. 8. Multi-resolution control scheme to adaptive the output force with the human in the loop.

given as,

$$H(q)\ddot{q} + C(q,\dot{q})\dot{q} + G(q) = \tau \tag{17}$$

where $\{q,\ \dot{q},\ \ddot{q}\} \in \Re^{n\times 1}$ represent the joint position and its derivatives, and $\tau \in \Re^{n\times 1}$ is the input torque vector. The dynamic force structure is defined by $G\,(q) \in \Re^{n\times 1}$ as a gravity vector, $H\,(q) \in \Re^{n\times n}$ is the inertia matrix, $C(q,\ \dot{q}) \in \Re^{n\times n}$ is the centrifugal or Coriolis matrix; with n degree of freedom. The joint friction dynamics is assumed to be zero.

$$H(q) = \begin{bmatrix} h_{11} & h_{12} \\ h_{21} & h_{22} \end{bmatrix}$$

$$C(q,\dot{q}) = \begin{bmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{bmatrix}$$

$$G(q) = \begin{bmatrix} g_{11} \\ g_{21} \end{bmatrix}$$

where:

$$h_{11} = \frac{l_1m_1+l_2m_2}{12} + \frac{l_1^2m_1+l_2^2m_2}{4} + l_1^2m_2 + l_1l_2m_2cos(q_2)$$
$$h_{12} = \frac{l_2m_2(3l_2+6l_1cos(q_2)+1)}{12}$$
$$h_{21} = \frac{l_2m_2(3l_2+6l_1cos(q_2)+1)}{12}$$
$$h_{22} = \frac{l_2m_2(3l_2+1)}{12}$$
$$c_{11} = \frac{-l_1l_2m_2\dot{p}_2sin(q_2)}{2}$$
$$c_{12} = \frac{-l_1l_2m_2\dot{q}_1sin(q_2)-l_1l_2m_2\dot{q}_2sin(q_2)}{2}$$
$$c_{21} = \frac{l_1l_2m_2\dot{q}_1sin(q_2)}{2}$$
$$c_{22} = 0$$
$$g_{11} = \frac{9.81(l_1m_1cos(q_1)+2l_1m_2cos(q_1)+l_2m_2cos(q_1+q_2))}{200}$$
$$g_{21} = \frac{9.81l_2m_2cos(q_1+q_2)}{200}$$

Using the same procedure for the extraction of characteristics of the EEG signals and finding that the greatest amount of information of the execution of force of the hands is found in the Beta band, the reference signal is defined as

$$y_{ref(j)} = \Omega U$$

where

$$U \in [0.15, 1.18]$$

Where for link $\Omega = 5000$, for link 2 $\Omega = 4000$ y $j$and indicates the number of inputs of the system for this particular case for this particular case $j = 2$, leaving the reference signal as,

$$Y_{ref}(t) = \begin{bmatrix} l_1 \cdot sin(y_{ref(1)} \cdot t) \\ (l_1 + l_2) \cdot sin(y_{ref(2)} \cdot t) \end{bmatrix}$$

The acquisition and processing of the EEG signals allowed to close the BCI system with the Multiresolution Proportional Control obtaining the following results; in Figure 9, the output of the system defined by the reference signal defined by the previous equation.

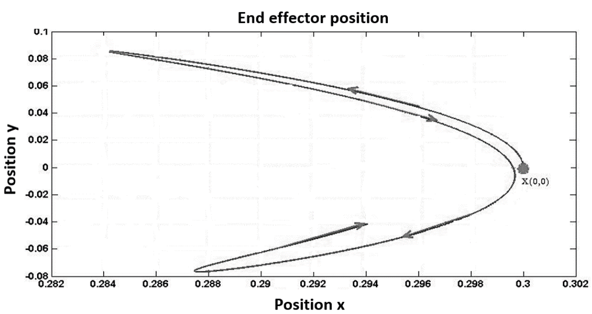

Fig. 9. Forward kinematics of position of the robot task with the human in the loop.

IV. Conclusions

In the present study, through a wavelet analysis using electroencephalography (EEG) recordings, it was found that the imagined force can be used for online control of robotic devices within the BCI (Brain-computer Interface) system. The result allows to lay the foundations for the control of human-robot interaction systems with a response associated with the user's intention as a control command; this represents an advance in adaptive control schemes, in which the structure or parameters are those that adjust to changes in the dynamics of the robotic system. Intelligent control techniques allow adapting the conditions of the required control gains according to the user, which represents a possibility of neurorehabilitation in patients with disabilities in the upper limb. The monitoring tasks in the robotic system are established from clinical protocols, and the modification of the movement parameters and force command are defined from the brain signals; to this end, the sensory analysis of neurological activities represents guaranteeing high performance in decision-making, as part of the method to solve control schemes with various complex applications not only in the rehabilitation area, but also in various industrial processes, among others.

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