# Brain–Computer Interface for Controlling Lower-Limb Exoskeletons

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## 9.1 Introduction

About 15 million people around the world suffer a stroke each year [1]. After a stroke episode, one or more effects may be triggered, such as muscle weakness, hemiparesis, hemiplegia, fatigue, and spasticity. Those affectations are related in turn to limitations in the execution of different activities of daily living, restriction in participation, and a high degree of dependency on third parties [2]. Therefore, stroke is one of the leading causes of physical disability directly affecting the quality of life [1].

Post-stroke rehabilitation is a patient-centered process to maximize patients' functional independence who have suffered a series of disabilities associated with the episode [3]. Assistive technologies for motor rehabilitation include exoskeletons and robotic orthoses, which may provide high motor intensity, repeatability, and

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precision [4]. However, one of the most critical problems that must be solved for the clinical implementation of these developments is their control systems.

Conventional control includes tools as inertial sensors, direct contact operation, and external transducers. However, despite the effectiveness of traditional control systems, some authors insist that these methods ignore the patient's involvement with the system regarding neurofeedback progression [5]. Thus, robotics-based rehabilitation becomes a process that does not fully exploit the patient's ability to generate neuroplasticity progressively, since neurological intend is not directly implicated [5].

In this way, given the rise of the Brain–Computer Interfaces (BCI) paradigm, many developments have focused their applications on motor rehabilitation and language assistance [6]. Control of exoskeletons and orthoses BCI-based has been extensively studied. Some research affirms that physical therapies involving BCI in patients with neuromotor conditions may improve their neuroplasticity more effectively [7]. There are many paradigms and modalities of BCI used in research; one of the most approached is Motion Imagery (MI) analysis, which is based on the electrical activity of the motor cortex that occurs when there is a movement intention of the subject [7]. This strategy seeks to improve the patient's interaction with the therapeutic mechanisms that pursuit an evolution of the neuroplasticity, adequately including the use of the neuromotor abilities through the BCI system in the rehabilitation process [8].

Following the above, this chapter discusses the main concepts of designing a BCI system in the robot-assisted rehabilitation field. To do so, the chapter is organized into seven sections. Section 9.2 conceptualizes the BCI term and electroencephalography (EEG) signals. Section 9.3 aims to present the stages in the universal design of a BCI system. Section 9.4 focuses on a literary review about BCI systems in lower-limb rehabilitation. Section 9.5 introduces the integrating control system for an ankle exoskeleton, based on the analysis of EEG signals and their involvement in the locomotor system. Section 9.6 addresses a case study with a post-stroke patient to evaluate the operation of a BCI control system for the exoskeleton control. Finally, the last section of the chapter presents conclusions and future works.

## 9.2 Brain–Computer Interface and Electroencephalographic Signals

Brain–computer interface (BCI) is considered a relatively novel communication method between a user and a machine. This communication may work as a control system in which human mind thoughts are translated into real-world interactions. Some recent studies have shown a significant role in future technologies for assisting people with disabilities [9, 10]. In rehabilitation and assistance technologies, the ideal BCI system is when a device may be controlled as naturally as using a human body limb [11]. To do this, BCI relies on EMG signals denoting the sum of the neurons' action potentials throughout receiving and processing sensory inputs from other neurons or external stimuli [12]. That means the EEG technology may accurately measure brainwave activity [13]. The way to access this physiological data is through sensitive electrodes attached to the scalp. The most common recording technique is the application of 21 electrodes and an equal number of channels. Other techniques include 256 electrodes and a number up to 64 channels [12, 13].

Even when there are other methods for extracting the brain activity, for instance, electrocorticograms (ECoGs) [14], magnetoencephalograms (MEGs) [15], functional magnetic resonance imaging (fMRI) [16], and near-infrared spectroscopy (fNIRS) [17], the popularity of EEG makes it widely used due to its non-invasive action, compatibility, portability, and its high temporal resolution in comparison with the mentioned methods above. Nevertheless, the EEG has a weak signal and is prone to several artifacts and relatively low spatial resolution [12]. This type of signal is generally in the order of microvolts ($\mu$V) range. Moreover, many investigations have categorized the EEG signals in the frequency domain, and until now, these ranges are divided into five main categories, which consists of delta ($\delta$) (0.5–4 Hz), theta ($\theta$) (4–8 Hz), alpha ($\alpha$) (8–13 Hz), beta ($\beta$) (13–30 Hz), and gamma ($\gamma$)(>30 Hz).

## 9.3 BCI Control System Design

Every BCI system has a basic structure. According to He et al. [5], there are four primary stages to construct a universal BCI system. The first one is the signal acquisition from the brain. The second one is the pre-processing stage of the signal mentioned above. The third stage refers to the processing, which includes feature extraction and decoding or translation. Finally, the last stage is the execution stage that puts the device into operation according to the human brain's intent (see Fig. 9.1).

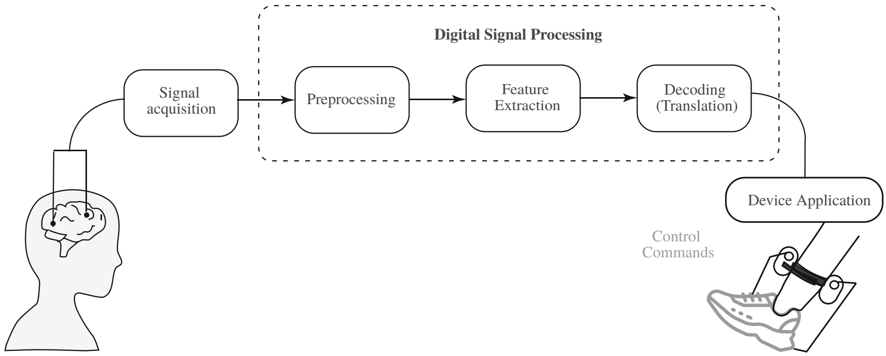


**Fig. 9.1** BCI basic system diagram that includes signals acquisition and processing

It is essential to add that the basic diagram could change in some aspects, for instance, depending on the system design. The following subsections will describe the general objective of each stage.

### 9.3.1 Signal Acquisition

As was mentioned above, EEG is the preferred tool to extract brain activity from the user. However, the signal acquisition process may be executed in numerous ways depending on the suitable BCI modality. These modalities could be classified into two categories: exogenous and endogenous [18].

- **Endogenous Modalities:** In this case, EEG acquisition is produced independently from external stimulation. Namely it may entirely be managed voluntarily by the user. This modality is mainly applied to subjects who have neurological issues [18]. In this manner, the BCI could offer a more natural and spontaneous way of interaction. Neuroplasticity is a fundamental feature that may be improved with this modality [19].

  For instance, Event-Related Desynchronization/Synchronization (ERD/ERS) works based on the behavior of brain signals and motor intent. Frequency bands may show a power increasing or decreasing when a subject imagines or executes a lower movement [7]. Evidence has been shown that the methods to detect lower-limb motor imagery with ERD/ERS usually focus on the potency of the beta rebound band of the EEG cortical due to an abrupt increase in the signal power just when the movement of the lower-limb ends [20] (see Fig. 9.2). This behavior occurs similarly at the end of the imagination of a movement. Other strategies as the Movement-Related Cortical Potentials (MRCPs) are based on a set of power variations in the cortical activity before and after the movement execution [21].
- **Exogenous Modalities:** An exogenous BCI refers to the generation of external stimuli to add more effectiveness. There are many types of stimuli where the most common are auditory and visual [18]. This modality implies simple training strategies compared with the endogenous modalities, necessary for the subject to drive suitably the BCI system.

  External instruments as the Steady-State Visual Evoked Potential (SSVEP) are used to excite brain signals based on a set of multiple visual stimuli, such as LEDs or figures on a computer screen [22]. Likewise, the Event-Related Potential: P300 in BCI applications forces the subject to focus on the selected item on the screen and ignore the rest [23]. In this case, the positive deflection appears approximately 300 ms after presenting an attended stimulus. Nevertheless, one issue found in all these exogenous modalities is that the subject cannot manage the entire device independently and is dependent on external conditions.

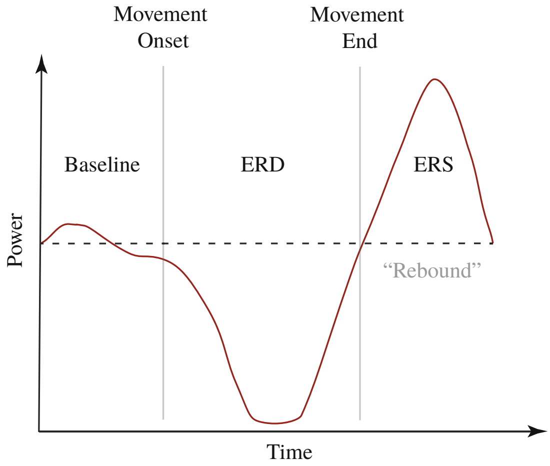


**Fig. 9.2** Event-related desynchronization/synchronization (ERD/ERS) power behavior

In addition to the endogenous and exogenous modalities, the hybrid BCI modality (h-BCI) combines the unique advantages of two different systems or signals to make the BCI control more effective, accessible, and optimal [24]. Some signals could be added as hybrid BCI (h-BCI) systems or feedback sources to improve rehabilitation or assistance aspects [25, 26]. According to Hong et al. [27], there are three objectives for implementing an h-BCI. The first one is to enhance classification accuracy. The second is to increase the number of brain commands for control application. Finally, the third objective is to achieve a shortened brain-command detection time.

An example of a signal hybrid modality is the union of electromyographic (EMG) signals with EEG, a promising alternative for rehabilitation therapies [28]. EMG signals indicate muscles' electrical activity, which changes when a voluntary or not voluntary contraction appears. Therefore, the EMG signal confirms a detection system for muscular movement [27]. That said, the incorporation of these signals depends on the task the subject performs. However, in any case, EMG control is used as an additional control system in biomechanical action. For instance, the laterality detection [27] and the biomechanical freedom degrees detection [29] could be pretty complicated with only an EEG-based system.

Another h-BCI modality could combine both ERD/ERS and SSVEP systems. Bunner et al. [30] have achieved a high accuracy system carrying this proposal out. Other authors have done experiments with this implementation, concluding that this modality does not need an exhaustive training process. Moreover, this modality could reduce the non-legible population by 20% [31]. The above shows an improvement in the most significant disadvantage of the ERD/ERS individual modality, where generally one part of the population is not eligible due to the intrinsic users' characteristics against distractor factors on BCI performance [32].

### 9.3.2 Pre-processing

Once a set of signals are obtained, it is necessary to consider that this set is generally entirely raw and full of artifacts depending on the technology used for this objective, the environment, and the user's physical conditions (e.g., noise related to the hardware, electrode wear, interference and skin impedance fluctuations) [33]. Therefore, denoising and cleaning the data is a widely studied process that already has numerous advances. For instance, the Filter Bank Common Spatial Patterns (FBCSP) is the most used method in BCI systems due to its efficacy in pre-processing signals and further stages [33, 34]. On the other side, according to Tariq et al. [35], interference issues could also be managed through digital filters as a notch filter. Likewise, other methods such as independent component analysis (ICA), principal component analysis (PCA), non-linear adaptive filtering, and dipole analysis have been tested.

### 9.3.3 Feature Extraction

After the signal pre-processing, this stage oversees classifying as many features as the BCI system requires. Some BCIs are based on Motor Imagery (MI) [7]; this modality is related to specific frequency bands. Therefore, its use depends on the suitable method to characterize these specific ranges for future decoding to build a set of commands necessary to control the target device [36].

Numerous feature extraction methods have been studied in BCI systems. However, these strategies depend on the modality structure. According to Lotte et al. [37], the extraction methods could be divided into three categories: (1) Time-domain analysis, (2) Frequency-domain analysis, (3) Time–frequency-domain analysis, and (4) Spatial complimentary analysis. One of the most used methods is instantaneous statistics and autoregressive methods (AA) in a time-domain analysis. Likewise, frequency-domain methods include Fourier Fast Transform analysis, Short Time Fourier Transform (STFT), and Power Spectral analysis. Frequency-time techniques, for their part, may span Wavelet Transform and Hilbert–Huang Transform (HHT). The fourth classification is the Common Spatial Patterns and has been widely used [37].

### 9.3.4 Decoding

The feature extraction layer forms a set of classification that the decoding stage uses to identify the intent brain signals, namely, to manipulate the robotic device via machine-understandable commands for interfacing [18]. The system generally works by making a weighted class estimate, presented by a feature vector for mapping the desired driving application command. Some of these strategies are Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), Gaussian Mixture Model (GMM), and Artificial Neural Network (ANN) [35].

## 9.4 Lower-Limb Exoskeletons with BCI Systems Review

This section introduces recent works on developing BCI Systems focused on the lower-limb robotic devices, the modality for signal acquisition, pre-processing strategies, and main results. Table 9.1 summarizes the principal data found in the research for each exoskeleton with a BCI integrated system.

### 9.4.1 Lokomat

*Lokomat* (Hocoma, Switzerland) is a robotic treadmill exoskeleton to automate locomotion training for spinal cord injured and stroke patients [38]. BCI system in *Lokomat* device was researched looking for the subject participation improvement. Initially, this orthosis worked in a training mode where the device influenced the subject's motion with a fixed gait pattern [38,39]. Even when some reports conclude this causes greater coordination of the muscles and the neuromotor system, BCI became an alternative to improving the device.

Donatti et al. [40] show some clinical assessments. Eight (8) chronic spinal cord injury (SCI) paraplegics were subjected to long-term training with a multi-stage BCI-based gait neurorehabilitation paradigm aimed at restoring locomotion. The BCI system modality was the MRCP. The Common Average Patterns method was used for pre-processing stage, including conventional digital filters for denoising. Moreover, the decoding process was based on Linear Discriminant Analysis (LDA) methods [40].

The methodology of these authors was composed of six parts, where the patient was addressed to familiarize the BCI with a tactile feedback system. Then this same familiarization continued in an orthostatic position supported by a stand-in table. Without using a BCI, they began conventional training with the *Lokomat* device, including body weight support (BWS) on the treadmill. Then a BWS training was continued without *Lokomat's* joint support. Finally, in sections the BCI was integrated into the gait training system supported by the tactile feedback system (on treadmill and overground, respectively).

After 1 year of training in the *Lokomat* BCI system, all eight subjects improved neurological motion and somatic sensation as pain and proprioceptive sensing. In terms of neuroplasticity, the research showed no significant differences between a desynchronization and synchronization of the beta wave from an event-related potential analysis at the onset of the training therapy period. However, after 10 months of therapy, these synchronization differences were observed in all patients. In terms of anatomic improvements, all patients exhibited a complete ROM of the joints and a maximal grade of lower-limb spasticity of 2 on the Ashworth scale. Furthermore, a test provided by *Lokomat* developers known as L-stiff was used. This test is in charge of quantifying the spasticity of hip and knee muscles for flexors and extensors. Thus, on average, all patients exhibited a reduced spasticity level by the end of 12 months.

**Table 9.1** Comparison of the paradigms, characteristics, and results of the BCI system applied to lower-limb exoskeletons

| Robotic device | Joints | Modality/paradigm | Pre-processing methods | Feature extraction methods | Decoding methods | Participants | Main results |
|---|---|---|---|---|---|---|---|
| *Lokomat* [38–40] | – Hip<br>– Knee<br>– Ankle | MRCP | – Common average patterns<br>– Temporal filters | N/I* | LDA | 8 SCI patients | – Neuroplasticity generation observed from significant beta wave de/synchronization<br>– The patients exhibit complete ROM joint after therapy<br>– Spasticity reduced |
| *RoGO* [41–43] | – Hip<br>– Knee<br>– Ankle | ERD/ERS<br>– Serious games feedback | Own prediction channels method | – Frequency analysis<br>– PSD<br>– PDA | AIDA | 1 Healthy subject<br>1 SCI patient | – 85% BCI commands accuracy<br>– 0.812 correlation between natural movement and BCI MI detection<br>– Average of 0.8 false alarms in BCI commands<br>– No omissions in BCI commands |
| *H2* [44, 45, 47] | – Hip<br>– Knee<br>– Ankle | h-BCI:<br>– ERD/ERS<br>– MRCP | – Z-scores method<br>– Temporal filters | – Laplacian spatial filter<br>– Common average patterns<br>– PDA | SDA | 3 healthy subjects<br>4 SCI patients | – 84% accuracy commands for a healthy subject<br>– 77% accuracy for SCI patient<br>– 55% false alarms commands or healthy subjects<br>– 40% false alarms command for SCI patients |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| *Rex* [48–50] | – Hip<br>– Knee<br>– Ankle | MRCP | – Z-scores method<br>– Temporal filters | Own method for delta wave isolation | MKL | 1 healthy subject<br>1 SCI patient | – A rise of accuracy BCI commands from 60% to 90% |
| *MAFO* [51] | – Ankle | MRCP | – Spatial filters<br>– Temporal filters | Local preserving projection | LDA | 10 healthy subjects | – 73% accuracy reported<br>– Feasible plasticity induction |
| *H2 Foot-Ankle Orthosis* [51] | – Ankle | – ERS/ERD<br>– FES feedback | – Temporal filters | PSD | Own classi-fication method | 5 healthy subjects | – 100% BCI-FES response (no omissions)<br>–Only one subject had one false alarm |

### 9.4.2 RoGo

*RoGo* (University of California, USA) is a robotic gait orthosis addressed to Spinal Cord Injury (SCI) patients [41]. This orthosis has been studied mainly with the BCI system control [41–43]. The BCI modality used in the investigation includes ERD/ERS induced by the kinesthetic motor imagination of the left hand, right hand, and feet. The pre-processing method is briefly described by Wang et al. [43] and includes an EEG prediction model that excludes those EEG channels with excessive artifacts. Two states were defined in the feature extraction method, Idling, and Walking states. Then this data was transformed in the domain frequency and their Power Spectral Densities. Moreover, a PCA algorithm was applied to reduce the data dimension. Finally, the researchers use the AIDA method to classify the commands to *RoGo*. Serious games have been implemented before a complete integration to the rehabilitation device. For instance, one experiment proposed to drive an avatar that expects to stop with a specific indication. The results gathered all the correct and wrong attempts and showed an 85% accuracy.

This system was assessed in a study by Do et al. [41] with a clinical assessment where patients with SCI impairments and one healthy subject were compared. The performance of this system was assessed by calculating the cross-correlation and latency between the computerized cues and BCI-RoGO response, and the omission and false alarm rates. The methodological protocol consisted of three divisions: (1) active walking (subject voluntarily walks while the *RoGO* servos are turned off ), (2) cooperative walking (subject walks synergistically with the *RoGO*), and (3) passive walking (the subject is fully relaxed while the RoGO makes walking movements). Those different training stages were helpful in set baseline values for EMG and EEG. Finally, the accuracy of the EEG prediction model averaged 86.30% across both subjects. The cross-correlation between instructional cues and the BCI-RoGO walking epochs averaged across all subjects, and all sessions were 0.812. Also, there were, on average, 0.8 false alarms per session and no omissions.

### 9.4.3 H2 Exoskeleton

*H2* (Technaid S.L., Spain) exoskeleton was developed in Spain and is addressed to stroke patients with gait impairments [44]. This device is aimed to assist and rehabilitate patients with suitable walking in a natural environment. According to the researchers, the exoskeleton has six joints, including the hip, knee, and ankle. Moreover, *H2* presents an open architecture that allows modifications in the control system [45, 46]. López-Laraz et al. [47] implemented a BCI control system with ERD/ERS-MRCP hybrid modality. Pre-processing methods are based on an automated procedure based on z-scores to eliminate the trials containing artifacts and conventional denoising filters. The ERD features were calculated after applying a small Laplacian filter to the frontocentral, central, and centroparietal EEG channels in terms of feature extraction. On the other hand, the Common

Average Patterns method was used for the MRCP modality. For the decoding process, a strategy named Sparse Discriminant Analysis (SDA) was used.

López-Laraz et al. [47] presented a clinical assessment where three (3) healthy subjects and four (4) SCI patients were tested. The basic system uses the BCI described above to trigger exoskeletons' assistive motion. Factors as fatigue and exertion level, usability, and user satisfaction were assessed. Results concluded for healthy subjects with approximately 84% of accuracy, and SCI subjects 77%. On average, 55 and 40% of the trials (for healthy subjects and patients, respectively) have suffered unexpected activations without the proposed control strategy.

### 9.4.4 Rex Exoskeleton

*Rex*(Rex Bionics Ltd., New Zealand) is an exoskeleton that aimed to assist rehabilitation and mobility for those with neurological and spinal injuries [48]. *Rex* has been developed for private users that can now perform tasks that are not possible when sitting in a wheelchair. Specifically, the exoskeleton aids the patient to improve git patterns and movement for standing and sitting [49]. A joystick system initially drove *Rex*, but some BCI systems were designed to include this device in the rehabilitation field [50] .

Zhang et al. [50] made an investigation with MRCP-based BCI implemented on the *Rex* exoskeleton. The authors included a filter in the 0.1–2 Hz range in terms of the pre-processing stage using a second-order Butterworth filter and standardized z-score method. In the feature extraction stage, isolation of the delta band was carried out. For the classification stage, a Multiple Kernel Learning (MKL) was used and compared with the SMV algorithm, where they conclude MKL was more suitable for the system. A clinical assessment was performed with two (2) subjects: one healthy subject and one with SCI impairment. Results conclude that the frontal/frontocentral regions were the most critical regions for classifying gait states of the tested subjects, consistent with the brain regions hypothesized to control lower-limb movements. Moreover, the classification accuracy increased, and the findings suggest cortical plasticity triggered by the BCI use.

### 9.4.5 Motorized Ankle–Foot Orthosis: MAFO

This study was carried out by Xu et al. [51], where a BCI system was applied to the *Motorized Ankle–Foot Orthosis (MAFO)*. The mentioned orthosis allows the assistance of the ankle dorsiflexion movement. The objective of this research was focused on the evaluation of the functionality of the BCI system commands and the verification of an increase in neuroplasticity in the subject. The paradigm chosen by the researchers was MRCP. Spatial filters and temporal filters were used as pre-processing. The processing means were defined by a Locality Preserving Projection (LPP) method in conjunction with the Linear Discriminant Analysis (LDA) decoding method.

The BCI system was evaluated through the manifestation of the subject on possible false commands or omissions. The rate of accurate detections was measured along with the rate of false commands per minute. In addition, subject monitoring was evaluated to verify her motor activity concerning MI. The results yielded 73% accuracy in the general system, weighting the values described. In terms of the induced plasticity, it was determined that there were significant differences before and after the tests that demonstrated induction of neuroplasticity in the subjects' cortical zone.

### 9.4.6 H2 Foot-Ankle Orthosis

This research led by Do et al. [52] does not include a robotic orthosis directly, but it is part of the research project that wants to improve the *H2* orthosis mentioned above. However, according to the research carried out, reports of this integration have not yet been carried out. Thus, a BCI system was integrated into a Functional Electrical Stimulation (FES) system, which potentially allows a robotic orthosis to be controlled in its dorsiflexion movement and, therefore, act like one. The digital processing of the signals was not described in detail, so they were limited to showing the acquisition process and the tests with the subject.

Five healthy subjects were evaluated, executing ten repetitions interspersed between dorsiflexion and relaxation. The BCI commands were intended to trigger the assistance caused by the FES system. The subject received signals to perform MI or remain at rest, with which the results of the system's functionality were observed. The results showed a correlation between the commands and the signals given to the subject of 0.77. Latencies were measured between the ranges of 1.4–3.1 s. Furthermore, no omissions were evidenced and only one subject had one false alarm.

## 9.5 BCI System Integration with T-FLEX

BCI Integration with *T-FLEX* (Colombian School of Engineering, Colombia) [53] emerges as a proposal that considers the patient's involvement with the system control through imaginary dorsiflexion movements. Thus, when the BCI system detects the activation, the user receives active movement through the robotic orthosis. In general terms, the integration system consists of the EEG signal acquisition system and the *T-FLEX* ankle exoskeleton (see Fig. 9.3). However, the process to command the device through EEG signals requires specific steps based on the theoretical concepts presented in the previous sections. Moreover, additional strategies are necessary for communication between systems.


**Fig. 9.3** Setup for BCI system integration with *T-FLEX*

### 9.5.1 Signal Acquisition

Electroencephalography (EEG)-based endogenous BCI is selected with an ERD/ERS modality. The objective is to extract characteristics located in the activity of the beta wave rebound power, whose frequency range is from 16 to 24 Hz. The acquisition system is achieved through *Enobio 20 Hardware* (Neroelectrics, Spain). This hardware is linked through the *NIC 2.0* (Neroelectrics, Spain) to allow the motor cortex recording with a Laplacian montage. This type of setup uses multiple electrodes at once as a reference. In this way, a single output channel is related to the neighbor electrode average of a specific electrode. In this case, the acquisition protocol takes as reference the Cz electrode of the international system 10–20. Thus, the output is the average of the acquisition channels C1, C2, FCz, and CPz.

Once the raw signal is acquired through the software, it is connected to a local server capable of transferring this data to the pre-processing, feature extraction, and decoding system. OpenVibe (Inria Rennes, France) is an open-use program that allows the implementation of different BCI modalities. According to the creators, the interfaces in OpenVibe reach a speed of up to 1 selection per 5 s with a selection accuracy of up to 70% in motor imagery [54].

### 9.5.2 Pre-processing

The pre-processing method was divided into two stages. The first one is applying a Laplacian filter, and the second one is based on a temporal filter. These implementations are described in more detail below.

- **Laplacian Spatial Filter:** This spatial filter calculates the second derivative of the instantaneous spatial voltage distribution for each electrode, and therefore focuses the activity originating from radial sources immediately below the electrode [55]. This tool highlights localized activity and reduces poorly defined activity. Moreover, this filter can create the best possible linear combination of the electrodes used to obtain a signal with less noise and maximized utility in the data [56].
- **Temporal Filter:** According to Clerc et al. [20], this filter is applied conventionally as a Butterworth-type band-pass filter, order 100 and with a 0.5 dB band ripple. Consequently, with the frequency range of the beta wave, whose behavior is essential for applying the ERS/ERD paradigm, the lower and upper cutoff frequencies were 16 and 24 Hz, respectively.

### 9.5.3 Feature Extraction

The feature extraction is based on the methodology proposed by Clerc et al. [20] to obtain a signal as straightforward as possible and represent the beta wave behavior in its motor synchronization and desynchronization periods. The process is performed in four steps:

1. Filtered signal decomposition into 1 s long epochs with an overlap of 100 ms between two consecutive epochs.
2. Signal square operation.
3. Signal's average calculation over the input epoch. The average of the signal is calculated for each interval of 1 s received from the previous step.
4. Signal crop to a minimum value. The minimum value was obtained by averaging and adding 3 times the standard deviation of the signal acquired during the 5-min calibration period.

### 9.5.4 Decoding

As mentioned above, the last step of the feature extraction consists of a calibration process that defines a potential threshold of the extracted beta rebound power. Thus, the potentials detected below the threshold value are taken as zero, while those that exceed it would be considered potentials of motion intend. Consequently, there is a proportionality between the intensity of movement and the potential magnitude generated by the beta rebound.

### 9.5.5 Communication Between Systems: BCI-T-FLEX

*T-FLEX* is a wearable ankle exoskeleton whose main objective is to assist patients with impairment in the foot-ankle complex. This ankle exoskeleton comprises an

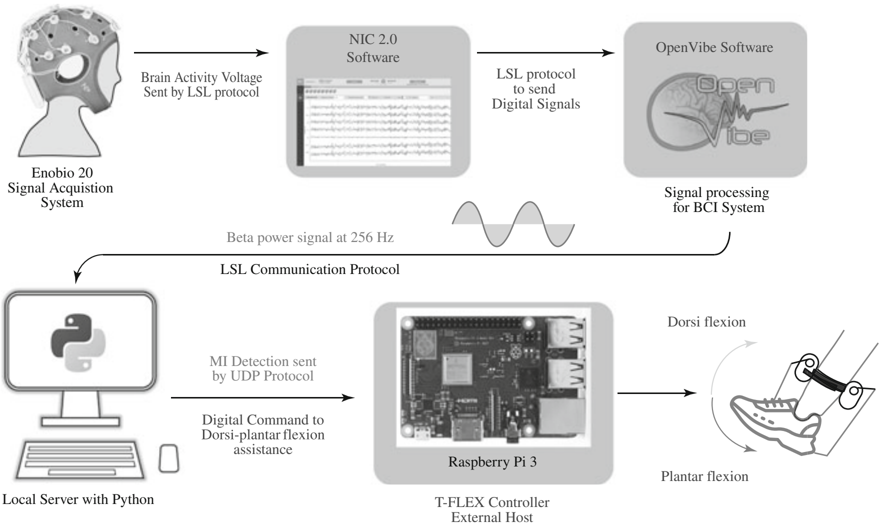


**Fig. 9.4** Communication protocol diagram involved in the BCI-T-FLEX integration system

actuator system with bioinspired tendons commanded by a Raspberry Pi 3 to assist gait or perform dorsi-plantarflexion repetitions in stationary therapy (see Chap. 6). Considering the above, communication between BCI System and *T-FLEX* is carried out directly from OpenVibe sending data continuously to the Raspberry Pi 3. However, this communication requires two sections: (1) output of the OpenVibe software to a local server and (2) a delivery of data from the local server to the external server of the robot controller (see Fig. 9.4).

1. **OpenVibe to Local Server Connection:** For this data extraction, the Lab Streaming Layer (LSL) protocol is used. OpenVibe uses a native LSL system, in which it is necessary to specify a name of a transmission channel and the type of signal to be sent. Once this channel was configured in the OpenVibe box system, a local server was created in Python, whose objective is to receive the transmission channel (i.e., an array of variables for each sample of the EEG signal, which includes sample number, time in seconds, channel, encoding type, and magnitude) (see Fig. 9.4).
2. **Local Server to *T-FLEX* Controller:** Once the data arrives continuously through the LSL channel which has a frequency of 256 Hz, this data will be processed to detect the exceeding of the previously defined threshold. This implies that the calibration process must be appropriately associated with the local server created in Python. In this way, every time a threshold is exceeded, the data will be sent as a logical “1” to the Raspberry Pi 3. This will cause an action equivalent to the dorsiflexion assisted by the robot. However, once a drop below the beta rebound signal threshold is detected, the local server will send a logical “0” to the controller, and it will remain in plantarflexion.

The communication protocol used to send this data was the User Datagram Protocol (UDP) connection that uses the IP address data of both parties to carry out a data exchange. In this case, it is an open-loop system that only sends unidirectional data to the *T-FLEX* (see Fig. 9.4).

## 9.6 Case Study: BCI System Control Assessment with T-FLEX

This case study presents the results of the BCI operation carried out with a post-stroke patient (age: 55 years, weight: 84 Kg, and height: 173 cm) with right hemiparesis laterality. This study seeks to evaluate the operation of a BCI control system for the *T-FLEX* exoskeleton and its preliminary effect on neurological activity. In addition to considering the EEG signal acquisition system and the *T-FLEX* ankle exoskeleton, the proposed system includes a visual interface with a full-screen that guides the actions to be carried out during the test using text instructions. The system integration test for the development of this case study was carried out in Club de Leones Cruz del Sur Rehabilitation Center with its corresponding Ethics Committee approval.

### 9.6.1 Experimental Procedure

The following procedure is based on experimental designs found in the literature [57]. The experiment is developed under three stages: During the first stage, 5-min calibration is performed while the participant remains statically in a chair with a 90° knee flexion. The second stage corresponds to a stationary therapy (ST) [58] where the EEG signal is recorded while the patient receives alternating dorsi-plantar flexion motion for 10 s using the *T-FLEX* robotic orthosis. Afterward, the last stage considers motor imagination with visual stimulation (MIV) to trigger the *T-FLEX* robotic device. The above implies EEG signal records while the patient imagines alternating dorsi-plantar flexion movement for 10 s while observing an image showing the desired command. The second and third stages alternate with 10 s-periods of rest until reaching a 5-min test.

Both experimental conditions (ST and MIV) involve the use of the *T-FLEX* exoskeleton. Therefore, capturing EEG records is essential to present a posterior comparative analysis in the brain activation frequency band (8–32 Hz). In this way, the quantitative characterization of the BCI system is performed employing the following variables at the end of the test:

- Accuracy rate: The data associated with the motor imagery attempts correctly detected by the BCI will be collected in the 10-s periods in which the patient is asked to imagine movement.
- Acquisition of EEG signals from a cortical zone: Continuous signals will be acquired at each test interval from the cortical zone, using channels Fcz, C1, Cz, C2, and Cpz International System. In this way, signal processing will be

carried out to compare and conclude if there are significant differences in the brain-motor activity of the patient when using the *T-FLEX* device integrated into the BCI system and in its absence. To conclude in this regard, the Event-Related Potential (ERP) methodology will be used.

### 9.6.2 Results of the Study

The result in terms of the accuracy level of motor imagery detection made by the patient was 53.33%. This result is a consequence of the difficulty of some people to perform motor imagination without prior training. As previously mentioned, this is one of the disadvantages regarding the ERD/ERS modality [32]. In this way, future studies should implement long training to guarantee better performance and control of the system. Figure 9.5 shows the temporal response for the isolate frequency band during one of the 10-s periods when the user was required to perform motor imagination.

Meanwhile, as can be seen in Table 9.0, the MIV test has a higher associated Power Spectral Density related with the Event-Related Potentials (ERP) in the Cz, C2, and Cpz channels vs. the therapy mode of the *T-FLEX* device, in which the patient was not required to generate motor imagery (ST).

The above is corroborated in the EEG topographies that tend to be oriented to increased brain activity on visual stimulation tests (see Fig. 9.6). These significant differences in brain activity between these tests may indicate the significant difference in the conventional therapy mode and the use of integrated BCI. Therefore, these results are helpful since they show a preliminary added utility in the proposed integration concerning the conventional use of *T-FLEX*. However, to generate a significant difference in motor imagery-related brain activity, the most viable paradigm for future research must include another kind of stimulation besides the visual.

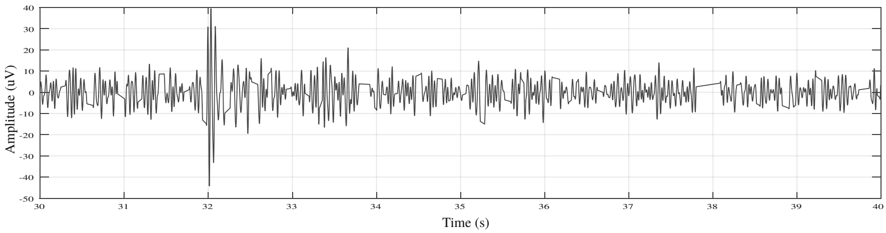


**Fig. 9.5** Cz channel filtered signal on the band 8–32 Hz in motion imagination detection state with visual stimulation to command the ankle exoskeleton

**Table 9.0** Power spectral density (PSD) associated with each channel in the ST and MIV test

| Test | Fcz | C1 | Cz | C2 | Cpz |
|---|---|---|---|---|---|
| ST PSD (dB/Hz) | 6.81 | 6.46 | 6.84 | 7.60 | 6.30 |
| MIV PSD (dB/Hz) | 7.75 | 7.66 | 7.61 | 8.83 | 7.19 |

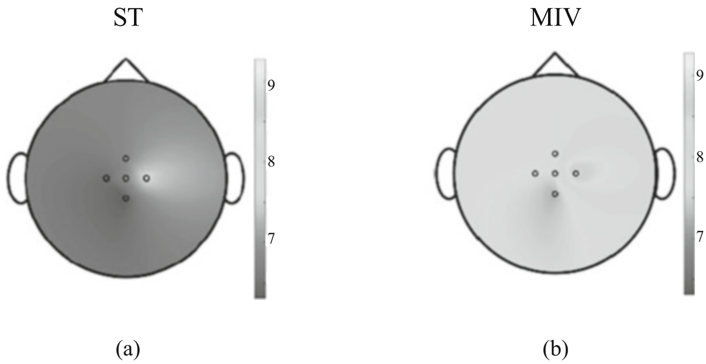


**Fig. 9.6** EEG topographies of power spectral density associated with the event-related potentials for tests with and without motor imagination. (**a**) Stationary therapy. (**b**) Motor imagination with visual stimulation

It is essential to mention that these results are partially beneficial for generating neuroplasticity in post-stroke patients [59,60]. However, this single-session test does not prove that neuroplasticity was generated or induced in the patient using this interface. According to long-term research, this can be demonstrated in therapies with BCI systems and exoskeletons lasting between 10 to 12 months with a weekly intensity session [40]. Therefore, this case study is limited to achieving immediate results related to partially beneficial brain activity.

## 9.7 Chapter Conclusions

State of the art and conceptualization carried out in this chapter made it possible to compile the basic concepts of BCI systems, modalities, and EEG signal analysis to detect motor imagination. Moreover, the review applied to exoskeletons aimed at lower-limb rehabilitation with BCI shows the long-term advantages of using these systems in rehabilitation therapy to induce neuroplasticity. On the other hand, the BCI control system design process considers multiple features to acquire and process signals.

Finally, the experimental procedure and case study presented with a post-stroke patient allows us to conclude that stimulation methods or long training are essential to induce patients to generate movement imagination in BCI systems. Nevertheless, the BCI-TFLEX system provides a better neuronal response than conventional therapy performed with *T-FLEX* independently.

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