Chapter 3

ARCHITECTURE AND METHODOLOGIES

3.1 Overview

The proposed system utilizes a Brain-Computer Interface (BCI) combined with Functional Electrical Stimulation (FES) to facilitate rehabilitation for patients with spinal cord injuries and other neurological disorders. This system is designed to interpret brain signals captured via EEG, focusing primarily on those generated by Motor Imagery (MI) of limb movements. These signals are processed in real-time to extract meaningful patterns that are then translated into commands to control the FES device. The FES unit stimulates the corresponding muscles, aiding in the execution of intended movements and thus contributing to motor recovery.

Methodologically, the system involves rigorous training sessions for users to control their brain signals effectively, adaptive algorithms that personalize the interface for individual needs, and stringent integration protocols to ensure seamless interaction between the BCI and the FES device. Extensive usability testing with targeted demographics ensures the system is user-friendly and effective, tailored to enhance user independence and improve quality of life through facilitated motor function restoration and home-based rehabilitation capabilities. This comprehensive approach promises to advance rehabilitation practices and offer a novel solution for those impacted by severe motor impairments.

3.2 Architectural Design

The architecture integrates advanced signal processing, machine learning for feature extraction and intent classification, and a feedback loop that provides users with real-time sensory or visual feedback. This feedback is crucial for reinforcing motor learning through neuroplasticity. Extensive usability testing with targeted demographics ensures the system is user-friendly and effective, tailored to enhance user independence and improve quality of life through facilitated motor function restoration and home-based rehabilitation capabilities.

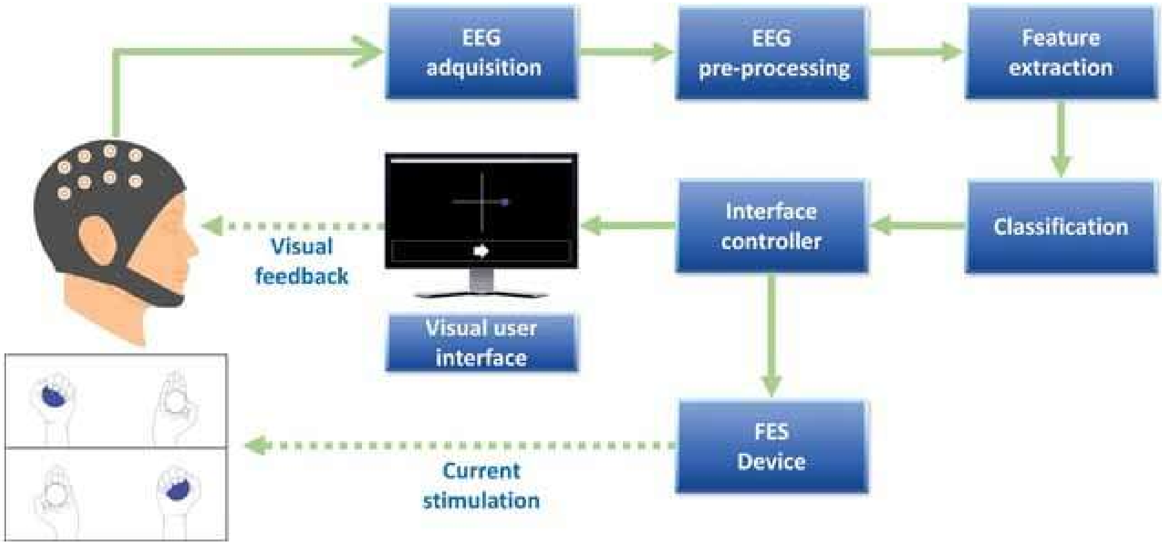

Fig 3.1: Architecture diagram of Brain Computer Interface

3.3 Module Description

Brain Computer Interface's architecture is designed to facilitate effective decision-making in reinforcement learning scenarios, enabling agents to master complex environments without prior knowledge of the environment's dynamics.

- **Data Acquisition and Preprocessing Module:** The Data Acquisition and Preprocessing Module serves as the initial stage of the system, responsible for capturing EEG signals from the user's scalp using non-invasive electrodes. Once acquired, these signals undergo amplification and digitization to prepare them for further processing. Subsequently, the module employs various preprocessing techniques such as band-pass filtering and artifact rejection to eliminate noise and unwanted signals, ensuring that only relevant brain activity is retained for subsequent analysis and interpretation.
- **Feature Extraction and Classification Module:** Following the preprocessing stage, the Feature Extraction and Classification Module extracts salient features from the pre-processed EEG data that correspond to motor intentions, particularly focusing on Motor Imagery (MI). Leveraging machine learning algorithms such as support vector machines (SVM), convolutional neural networks (CNN), or recurrent neural networks (RNN), this module classifies EEG patterns in real-time. Through continuous adaptation based on user feedback, the classification model enhances its accuracy and

adaptability over time, enabling more precise interpretation of user intent.

- **Control and Command Generation Module:** The Control and Command Generation Module acts as the intermediary between the decoded EEG patterns and the Functional Electrical Stimulation (FES) device. Upon classification of EEG signals, this module translates the identified motor intentions into stimulation commands tailored to the FES device. It determines the timing, intensity, and duration of stimulation based on the decoded user intent, ensuring precise synchronization between neural detection and muscle stimulation to facilitate accurate and coordinated limb movement.
- **Functional Electrical Stimulation (FES) Module:** The Functional Electrical Stimulation (FES) Module is responsible for executing the stimulation commands generated by the Control and Command Generation Module. Upon receiving these commands, the FES device delivers electrical impulses to targeted muscles through electrode arrays. By inducing muscle contractions that mimic natural movement patterns, the FES module aids in the execution of desired motor tasks. This direct brain control of limb movements not only facilitates motor rehabilitation but also promotes neuroplasticity and motor recovery over time.
- **Rehabilitation Protocol Module:** The Rehabilitation Protocol Module customizes rehabilitation protocols based on individual user needs, goals, and progress. Incorporating evidence-based rehabilitation strategies and motor learning principles, this module optimizes rehabilitation outcomes. Additionally, it facilitates home-based rehabilitation by providing guided exercise routines and progress tracking functionalities, empowering users to take control of their rehabilitation journey.
- **User Interface Module:** The User Interface Module offers a user-friendly interaction platform for seamless engagement with the BCI-FES system. Users can initiate training sessions, monitor their progress, and adjust system settings through intuitive interfaces. Visualizations of EEG signals, classification results, and stimulation parameters enhance user understanding, fostering active participation in the rehabilitation process.

3.4 Results

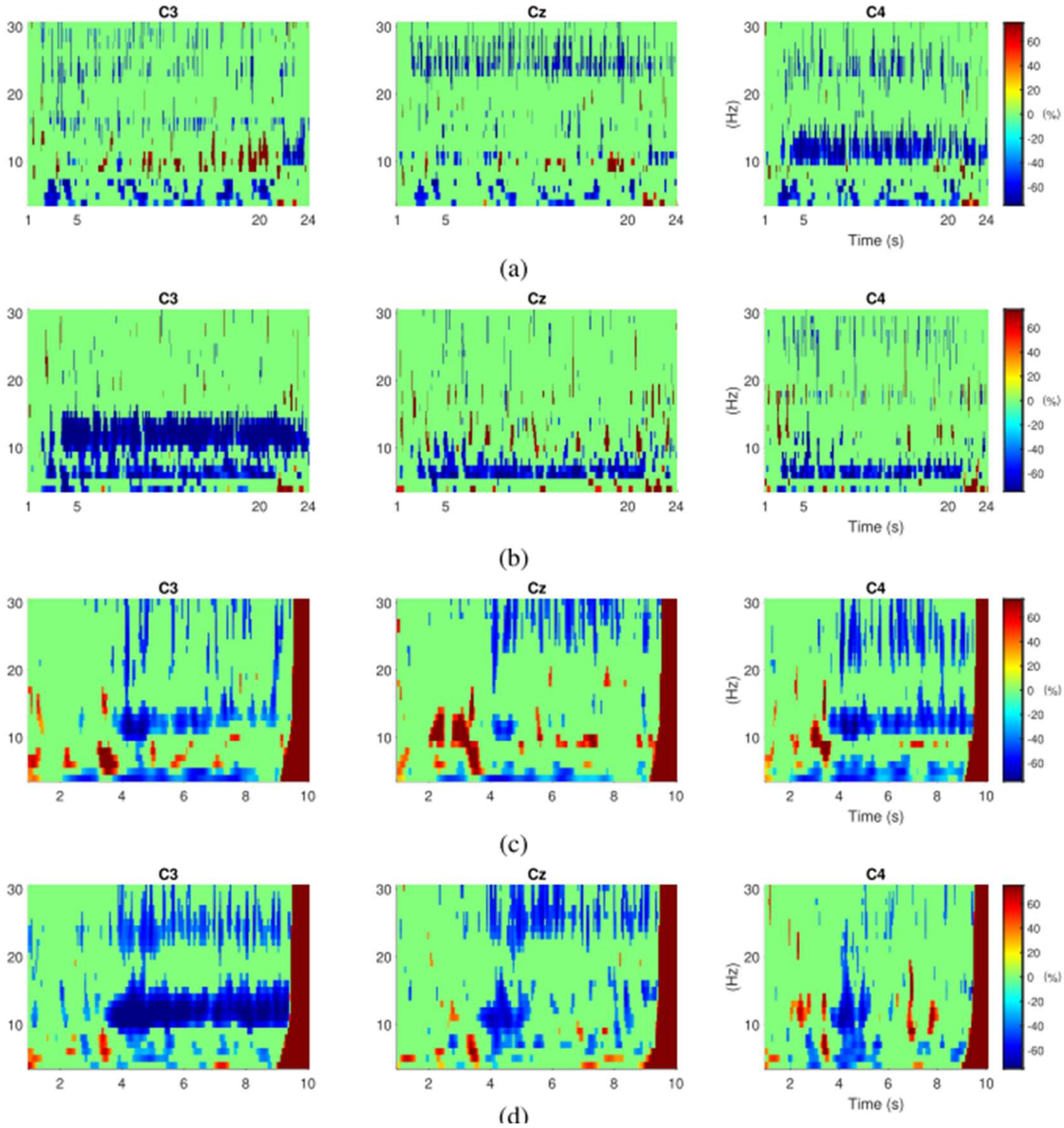

Fig 3.3: Significant event-related desynchronization/synchronization

Those electrodes were the only ones that showed significant correlation. For the channel C3 there was a significant negative correlation for αERDSrate and βERDSrate indexes in the online validation stage for Right MI ($p = 0.002$, $r = -0.543$ and $p = 0.019$, $r = 0.434$, respectively). For the Cz channel there was only a significant correlation for θERDSrate ($p = 0.035$, $r = -0.486$) in the calibration stage for Left MI. For C4 there were significant negative correlations for αERDSrate and βERDSrate in the online validation stage during Left MI ($p = 0.024$,$r = -0.418$ and $p = 0.023$, $r = 0.422$, respectively). For the channel C4 in the training stage, there were not significant correlations for all computed indexes. Note that significant correlations in channels C3 and C4 are related to the respective contralateral MI condition. Figure 6 displays the Pearson's correlations computed between C3 and C4 rERDSrate scores, calculated across all participants data, with FES activation time, separately for Right and Left MI, in the online validation trials. Figure 6a corresponds to αERDSrate correlations between channel C3 with FES activation time in the Left MI trials. For this case, a negative significant correlation ($p = 0.002$, $r = -0.543$) was observed. Figure 6b corresponds to αERDSrate correlations between channel C4 and FES activation time in Right MI trials. Also, a negative significant correlation was obtained ($p = 0.024$, $r = -0.418$) in this case. In general terms, these results show that higher scores of αERDSrate (near to 1) were related to shorter activation times of the FES routines.