Hand Rehabilitation System Using Functional Electrical Stimulation (FES) Based on Brain-Computer Interface (BCI)

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***Abstract*—Hand function impairment, including paralysis or muscle weakness (paresis), often results from neurological disorders such as stroke, spinal cord injury, and traumatic brain injury. It can significantly diminish patients' quality of life by limiting their ability to perform daily activities. Existing rehabilitation technologies, while beneficial, often fail to accommodate diverse patient needs due to factors like cost, usability, and their inability to incorporate patient intentions into therapy. To address these challenges, we propose an innovative rehabilitation system that integrates Brain-Computer Interface (BCI) technology with Functional Electrical Stimulation (FES). Utilizing the Motor Imagery technique, the system captures brain electroencephalography (EEG) signals, which are classified by an Artificial Intelligence (AI) model to interpret the user's intended hand movements. The classified signals are then used to activate an FES device, which stimulates the relevant muscles to execute the desired motion. This process is enhanced by a real-time feedback glove, ensuring accurate movement execution. Our rehabilitation system, combining BCI and FES, enhanced patient daily activity performance. Real-time feedback glove and adjustable FES parameters significantly improved rehabilitation outcomes. Additionally, our developed GUI monitors all system parameters, allows EEG recording, and maintains a patient database with an electronic report. This report helps patients track their progress and contains essential information from their clinicians.**

Keywords*—Artificial Intelligence (AI), Brain Computer Interface (BCI), Functional Electrical Stimulation (FES), Hand Rehabilitation, Internet of things (IoT), Motor Imagery techniques.

I. Introduction

Hand impairment and disability are commonly associated with neurological disorders such as stroke, spinal cord injuries, and brain injuries. For example, over 9 million stroke patients suffer from long-lasting hand disability annually. Spinal injuries also affect about 250,000 to 500,000 people annually causing serious movement dysfunction. Disability interferes with patients' ability to perform tasks, greatly reducing their quality of life and independence[1], [2], [3].

Many rehabilitation technologies address hand function impairment. These include virtual reality based exercises, mechanical grippers, exoskeleton gloves, and functional electrical stimulation (FES). While these solutions provide various degrees of assistance, they often fail to integrate the brain's control effectively, limiting their potential to fully restore hand function. This may lead to prolonged rehabilitation periods and reduced patient autonomy[4], [5].

To overcome these limitations, we propose a rehabilitation system that integrates Brain-Computer Interface (BCI) technology with FES. The BCI system captures the brain's signals through Motor Imagery techniques and classifies them using Artificial Intelligence (AI) models. These classified signals are then used to stimulate the corresponding muscles in the hand via FES, enabling the intended movements. This integration aims to facilitate the recovery of hand functions effectively and to enhance neuroplasticity[6], [7].

We incorporated a real-time feedback glove that monitors executed movement and provides immediate feedback. This feedback loop is essential for reinforcing correct movements and adjusting the system's responses based on the patient's performance.

All system components are interconnected through an Internet of Things (IoT) platform, managed via a user-friendly Graphical User Interface (GUI). This comprehensive approach not only improves the accuracy and effectiveness of the rehabilitation process but also provides detailed progress reports accessible to both patients and healthcare providers.

II. Related Work

The use of rehabilitation technology in restoring hand function is significant. Traditional methods, such as exercises, have long been the foundation of recovery. However, these approaches often require considerable time and patient effort without necessarily involving patients' active participation.

FES systems are widely used to enable users to manipulate objects using various grasp strategies. However, they do not account for user intention using natural pathways, besides other challenges[8], [9].

Combining BCI with FES in restoring impaired function due to paralysis. These systems have demonstrated high accuracy in interpreting user intentions and facilitating movements. However, issues such as artifacts in EEG signals, the need for long-term monitoring, and challenges in maintaining data quality and system reliability need to be addressed to enhance their effectiveness[10], [11].

Our project builds on combining the advantages of both BCI and FES and minimizing their challenges by utilizing AI and IoT technologies to enhance the rehabilitation process and improve the quality of life for patients with hand dysfunction.

III. Methodology

A. Dataset Description

This study utilizes two data sources: a public online dataset and our own collected data.

1) Public Online Dataset:

Clinical Brain-Computer Interfaces Challenge WCCI 2020 Glasgow dataset includes EEG data from 10 hemiparetic stroke patients with impaired left or right hand finger mobility. All training files have 80 trials, 12 EEG channels, and 4096 samples per trial (8 seconds at 512 Hz). Channels follow the 10-20 international system: F3, FC3, C3, CP3, P3, FCZ, CPZ, F4, FC4, C4, CP4, and P4[12].

2) Collected data:

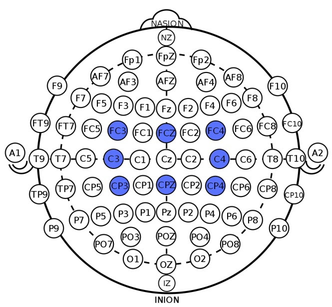

Fig. 1: Electrodes Placement of BCI Device

a) Neuron Spectrum: For our study, EEG data was collected using the Neuron Spectrum-4/P EEG device. The device recorded data at a sampling rate of 500 Hz and employed a notch filter to remove power line interference. As shown in Fig.1, The EEG setup involved nine channels following the 10-20 international system: C3, CZ, C4, FCZ, FC3, CP4, CPZ, CP3, and FC4. Additionally, FPZ was used as the reference channel, and the ground electrode was placed at the mastoid (Fig 1).

b) Participants and data collection Protocol: Data were collected from three subjects, during two separate sessions. In each session, distinct motor imagery tasks were performed: Hand Grasp Imagination, Hand Release Imagination, and a Baseline condition[13]. Each of the three tasks consisted of 30 trials, resulting in a total of 90 trials per session. Each trial lasted 6 seconds, and the tasks were presented randomly to ensure unbiased data collection.

B. Brain-Computer Interface (BCI) Module

1) Pre-processing: To improve the signal-to-noise ratio, focusing on the relevant frequency components, we applied the following:

a) Baseline Correction: We removed DC offsets and slow drifts by subtracting the average signal value during a baseline period from each data point[13].

b) Band-Pass Filtering: A band-pass filter (7-32 Hz) was used to retain the alpha (8-13 Hz) and beta (13-30 Hz) bands, crucial for analyzing motor imagery-related neural activity[13].

c) Trial Trimming: The first and last seconds of each trial were removed to eliminate any event-related effects, such as the order to start or stop imagination, ensuring the extraction of the most relevant signal segments.

2) Feature Extraction: We utilized two methods for extracting features:

a) Common Spatial Patterns (CSP): Used to extract features from the denoised EEG data maximizing the variance between two classes and enhancing discriminative power [14].

b) Filter Bank Common Spatial Patterns (FBCSP): We used FBCSP, which applies CSP across multiple frequency bands providing detailed and discriminative features and with higher efficiency and better performance than CSP[15].

3) AI algorithms: We utilized two different approaches for EEG feature extraction and classification:

a) *Deep Learning:* Initially, we used the EEG Inception motor imagery CNN architecture for EEG feature extraction and classification. This model is specifically designed to capture intricate patterns in EEG data, providing robust feature extraction and classification capabilities[16].

b) *Machine Learning (ML):* We utilized multiple ML models to classify the extracted features. These included: Support Vector Machine (SVM); Multilayer Perceptron (MLP); Linear Discriminant Analysis (LDA); Logistic Regression; and Extra Trees Classifier.

Each model achieved high accuracy individually. Additionally, we utilized ensemble learning through a hard voting classifier, combining the outputs of the five trained models using grid search to optimize performance.

C. Functional Electrical Stimulation (FES) Module

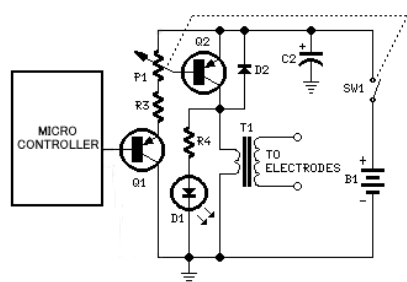

Fig. 2: Functional Electrical Stimulation Circuit Diagram

The FES module is designed to stimulate muscle contraction through electrical impulses. This FES system is a versatile two-channel surface stimulator that includes various components: software, a portable stimulator equipped with a programmable chip card, and self-adhesive stimulation electrodes (Fig. 2). This module is also distinguished by its fast and efficient setup process, usually taking around 5 minutes for complete customization.

1) System Capabilities and Customization:

The software component of the FES system offers extensive customization capabilities. Users can adjust stimulation parameters including frequency, intensity, and pulse duration. Additionally, the software allows for the modification of user interaction types and the number of repetitions, tailored to meet individual therapeutic needs. Moreover, this system features adjustable electrode placement, enabling personalized configurations for each patient.

2) Hand Function Therapy Protocols:

The FES allows precise training of various patterns such as Palmar Grasp (Holding an object like a ball); Tripod Grip (Using the thumb, index, and middle fingers to hold a pen); and Lumbrical Grip (Using all four fingers with the thumb to hold a closed book)[8].

3) System Parameters:

The FES system utilizes balanced, biphasic, current-regulated TENS electrical pulses to stimulate muscle contractions. During continuous stimulation mode, typical stimulation parameters include pulse amplitudes ranging from 8 to 80 mA, a pulse width of 250 µs, and a pulse frequency of 40 Hz[8].

4) Output signal & safety characteristics: safety measures included are:

a) Isolation Transformers: prevent direct electrical connections between a power source and the patient, enhancing safety and blowing a fuse in case of a short circuit.

b) Diodes: protect circuits by blocking excess current, ensuring only safe levels pass through, and minimizing reverse leakage.

c) X9C103 Digital Potentiometer: syncs with the microchip, controlling signal intensity smoothly and preventing sudden changes for safety.

d) Software Protection: ensure safety using PID feedback from digital potentiometers.

5) General considerations in applications of FES:

FES therapy's duration and frequency prescribed by the clinician is crucial to achieving the best results and sustained recovery.

Stimulation conditions such as duration, waveform, pulse frequency rate, intensity, and width are vital parameters during FES. The pulse width is particularly important and is safely capped at 300µs by both the software and hardware. Before each session, the stimulation level is calibrated by applying a consistent signal, and the voltage is gradually increased using a potentiometer to achieve the desired intensity.

D. Real-Time Feedback Glove Mechanism

We designed and developed a specialized feedback glove equipped with sensors and a magnetic field detection system. The glove measures fingers angles following stimulation to ensure proper execution of the intended motion[17].

1) Glove Design

The glove is crafted to be comfortable, lightweight, and flexible, facilitating ease of use during rehabilitation sessions and ensuring comfort even during extended wear[18].

The glove's functionality is based on the "hall effect" sensor, which is placed along the fingers to detect changes in the magnetic field caused by finger movements in relation to a reference magnet. When users bend their fingers, the relative position between the magnet and the sensors shifts, altering the magnetic field. The sensors measure these changes in magnetic flux density, providing comprehensive coverage of hand movements by being distributed across all fingers[19].

2) Mapping System

The data captured by the sensors is processed and analyzed to determine if the hand movements are a proper response to the FES. Calibration and mapping algorithms establish a direct link between sensor readings and the intended movements.

E. System Integration & Communication Flow

The integration is performed throughout seven messages where Message 1 (FES initial parameters) and Message 2 (Glove calibration) are performed one time for each session while the rest of the messages are sent continuously (Fig. 3).

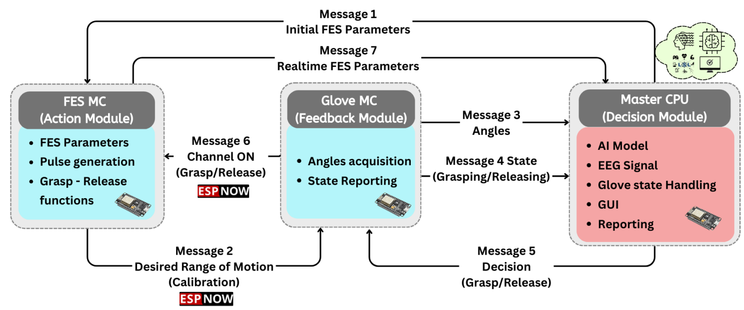

Fig. 3: Messages transmitted through Modules Diagram

The system involves a coordinated interaction between three primary modules: the Master CPU (Decision Module), the FES MC (Action Module), and the Glove MC (Feedback Module), These modules communicate wirelessly using User Datagram Protocol (UDP) communication and ESP-NOW protocol due to its low-latency and reliable data transmission.

1) Master CPU (Decision Module): The central processing unit of the system that is responsible for several functions.

a) EEG Signal Processing and AI Model: Uses the Lab Streaming Layer (LSL) protocol to receive EEG signals and the AI model to analyze motor imagery patterns to identify user intentions.

b) Glove State Handling: Manages the operational state of the glove, ensuring proper feedback is provided.

c) Graphical User Interface (GUI): Provides an intuitive interface for monitoring and controlling systems.

d) Reporting: Gathers and presents performance data and system logs for analysis.

2) FES MC (Action Module): Stimulates the grasp and release actions.

a) FES Parameters: Manages the intensity required for efficient function performance.

b) Pulse Generation: Produces the electrical pulses necessary for muscle stimulation.

c) Grasp-Release Functions: Executes the commands for grasp and release actions based on the decision from the Master CPU.

3) Glove MC (Feedback Module): It provides real-time feedback on the user's hand movements, for evaluating performance and reporting movement state:

a) Angles Acquisition: Continuously measures and reports the angles of the user's fingers.

b) State Reporting: Indicates the current state of the glove, whether it is in grasp or release mode.

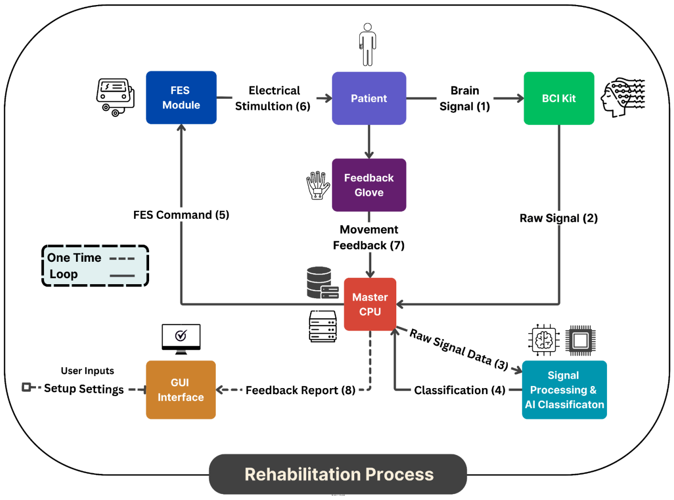

Fig. 4: System Block Diagram

IV. Results and Discussion

Our proposed rehabilitation system integrates BCI technology with FES to improve patient's quality of life by increasing their ability to perform daily activities due to its high usability and their ability to incorporate patient intentions into therapy.

We evaluated the performance of our AI models using a public online dataset[12] to validate model effectiveness. Our results (Table 1) showed that for within-subject models, traditional ML (FBCSP + LDA) performs better due to the variations in brain signals between subjects, which makes it challenging for a generalized model to capture the unique features of each subject. However, for cross-subject models, deep learning (EEG Inception MI) outperforms traditional methods, as deep learning models benefit from larger datasets and can generalize better across different subjects.

Model	FBCSP + LDA	EEG Inception MI
Within Subject	0.85	0.77
Cross Subject	0.70	0.88

Table 1. AI model validation using the "Clinical Brain-Computer Interfaces Challenge WCCI 2020 Glasgow" online dataset

Given these findings, we opt to use the ML within-subject approach for our system. This decision is based on the practical constraint of collecting a large amount of data from patients who need treatment with our system. Therefore, the ML approach is more feasible and effective for personalized rehabilitation.

For our collected dataset, we combined the Filter Bank Common Spatial Patterns (FBCSP) feature extraction method with several ML models. These models were then combined using a hard-voting ensemble classifier to achieve the best results as shown in Table 2.

Initially, we trained the models using the entire 4-second window of EEG data. We then experimented with reducing the window size to 2 seconds to observe any changes in accuracy. The results indicated only a small decrease in accuracy (<3%). Thus, the 2-second window was employed to reduce prediction time.

We observed that accuracies differed across subjects (table 2), reflecting individual differences in their ability to imagine motor tasks and environmental sources of artifacts such as their hair length. This variability underscores the importance of personalized models in achieving higher accuracies. The hard-voting ensemble classifier provided a balanced approach, leveraging the strengths of multiple models to optimize performance.

Subject	Evaluation Metrics	SVM	MLP	LDA	Logistic Regression	Extra Trees	Hard Voting
Sub1	*Accuracy*	**0.88**	0.83	0.83	0.83	0.79	**0.83**
	Kappa	**0.75**	0.67	0.67	0.67	0.58	**0.67**
Sub2	*Accuracy*	0.77	0.81	0.73	0.77	**0.85**	**0.77**
	Kappa	0.55	0.62	0.47	0.54	**0.69**	0.55
Sub3	*Accuracy*	0.69	0.72	**0.77**	**0.77**	0.70	**0.77**
	Kappa	0.38	0.44	**0.53**	**0.53**	0.4	0.53
Mean	*Kappa*	0.56	**0.58**	0.56	**0.58**	0.56	**0.58**
	Accuracy	0.78	**0.79**	0.78	0.79	0.78	**0.79**

Table 2. Validation of different AI models on the collected data

After implementing the FES system, we built the device from scratch and modified existing systems. Our custom-built circuit, with a 40 Hz pulse frequency and 8-50 mA amplitude range, effectively stimulated target muscles. Using real-time feedback to vary stimulation parameters significantly improved rehabilitation outcomes compared to fixed parameters.

Our FES system is integrated with a GUI and a feedback glove. This integration facilitates precise control and monitoring of the therapy, ensuring that parameters can be tailored to individual patient needs.

V. Conclusion

We developed an advanced hand rehabilitation system integrating BCI technology with FES. Utilizing the FBCSP feature extraction method and a hard voting classifier, we achieved an average prediction accuracy of 79% for real-time predictions using a 2-second window of EEG data. This system enables effective hand grasp and release rehabilitation based on users' intentions and is enhanced by a real-time feedback glove. Additionally, a user-friendly GUI is provided for reporting, session control, and monitoring, ensuring a comprehensive and responsive rehabilitation experience. While the system shows potential for enhancing patient daily activity performance, more data is needed to improve model accuracy. The FES circuit can be modified for better control, and the glove design requires more sensitive sensors to reduce delay. Moreover, the overall system would benefit from expert handling and a training phase for optimal use.

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