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EEG-BASED BRAIN–COMPUTER INTERFACE SYSTEMS FOR EXOSKELETON CONTROL: A REVIEW WITH CONCEPTUAL INSIGHTS

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ABSTRACT

This paper presents a comprehensive review of EEG-based Brain–Computer Interface (BCI) systems, with a focus on mental command recognition and its integration into human–machine interaction platforms. Recent advances in machine learning and deep learning techniques have enabled the translation of raw EEG signals into meaningful commands, facilitating control over robotic systems, assistive technologies, and exoskeletons. Key EEG paradigms such as motor imagery (MI), steady-state visual evoked potentials (SSVEP), and P300 are explored in detail with respect to their signal characteristics, classification challenges, and application performance.

We further propose a conceptual framework for a BCI-assisted exoskeleton system aimed at assisting individuals with lower-limb motor impairments. The proposed architecture includes signal preprocessing, feature extraction via discrete wavelet transform and autoregressive modeling, and classification using CNN, LSTM, or SVM algorithms. Wireless communication platforms like OpenViBE and Raspberry are recommended for real-time signal processing and device control. Although the proposed system has not yet been implemented experimentally, referenced studies demonstrate the feasibility of such applications with reported classification accuracies exceeding 90%.

The study also compares deep learning architectures—including CNN, RNN, LSTM, Autoencoder, and Transformer networks—highlighting their strengths and limitations for mental command recognition. Practical examples from the literature, such as EEG-based control of wheelchairs, robotic arms, and drones, are summarized to showcase the real-world potential of BCI systems. This paper aims to guide future work in designing personalized, low-latency, and high-accuracy EEG-based interaction systems, with a particular focus on rehabilitation technologies and cognitive augmentation.

Keywords: Electroencephalography (EEG), Brain-Computer Interface (BCI), Deep Learning (DL), Signal Processing

INTRODUCTION

Electroencephalography (EEG) is a non-invasive technique that enables time-sensitive measurement of the brain's electrical activity, and it stands out as one of the most accessible neurophysiological tools for directly observing neural functions[1]. Due to its high temporal resolution, low hardware cost, and portability, EEG has found extensive use not only in clinical diagnostics and neurological assessments, but also in real-time cognitive state monitoring, attention detection, and mental state classification[2].

In recent years, significant advances have been made in processing the complex structure of EEG signals using artificial intelligence (AI), particularly through machine learning (ML) and deep learning (DL) algorithms[3]. These approaches have enabled the translation of EEG signals into mental commands, which in turn can be used to control external systems.

In this context, **brain–computer interfaces (BCIs)** have emerged as innovative technologies that allow individuals to control computers, prosthetic devices, robotic systems, or other electronic apparatuses solely through their mental activity. BCI systems can recognize a range of commands by analyzing EEG-based signal sources such as motor imagery (MI), evoked potentials (e.g., P300, SSVEP), and rhythmic cortical activity.

As illustrated in Figure 1, these techniques have particularly expanded communication and control capabilities for individuals with physical impairments, while also redefining the boundaries of human–machine interaction. However, several challenges remain, including the inherently low signal-to-noise ratio of EEG data, inter-subject variability, and limited spatial resolution—each of which constitutes a major constraint on BCI system performance.

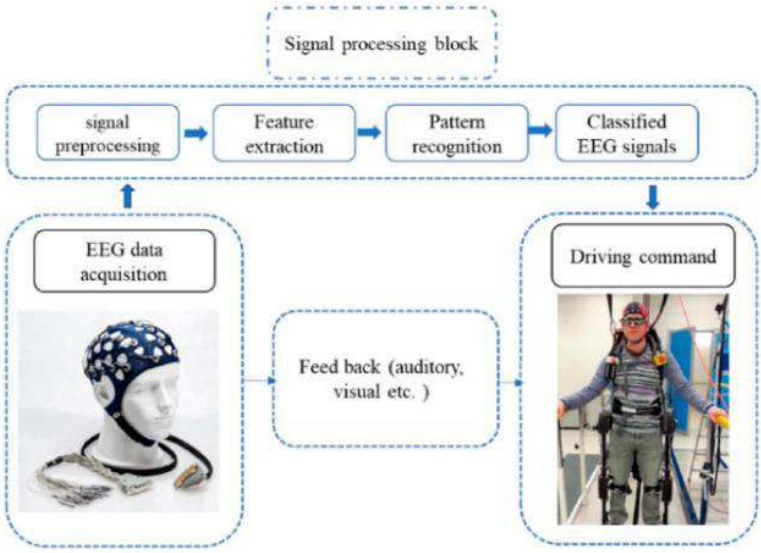


Figure 1. EEG - Motor Control [3]

This paper examines the role of EEG-based mental command recognition systems in human–machine interaction. It provides a comprehensive evaluation of the fundamental approaches in this domain, including the employed BCI techniques and contemporary artificial intelligence methods, in order to highlight the current state of progress in the classification of mental commands.

CONCEPTUAL FRAMEWORK

Characteristics And Processing Of Eeg Signals

EEG signals are generally characterized by low amplitude (in the microvolt range) and a high level of noise; therefore, their processing requires multi-stage preprocessing, filtering, and feature extraction techniques[4].

Fundamentally, EEG signals can be categorized into two groups: spontaneous signals and evoked potentials. Spontaneous EEG comprises naturally occurring signals that arise during states such as rest, sleep, or internal thought, whereas evoked potentials are more structured signals elicited by external stimuli, as observed in paradigms like motor imagery, P300, or Steady-State Visual Evoked Potentials (SSVEP). Among these, SSVEP provides a particularly stable form of EEG activity due to its frequency-locking property and relatively high signal-to-noise ratio[3,4]. When the eyes are exposed to visual stimuli flickering at a specific frequency, the resulting EEG responses exhibit strong energy at corresponding frequency components, producing distinctive and reproducible patterns unique to each individual.

However, EEG signals are subject to significant variability due to inter-individual neurophysiological differences, environmental conditions, and session-to-session fluctuations. This variability poses a major challenge to model generalization, especially in applications such as biometric identification and mental command systems. To overcome this issue, modern EEG-based systems increasingly adopt methods aimed at extracting invariant features in the frequency domain, which are more robust to temporal variations[4].

In recent years, modeling EEG signals using a multi-subband approach and prioritizing frequency components via attention mechanisms has significantly improved the performance of deep learning architectures, such as the Attentive Multi-subband Depth Identity Embedding Learning Network (AMDIELN). These models capture deep spatial and temporal features of EEG data, enabling the extraction of identity-relevant information that remains stable across sessions. Frequency-domain features such as power spectrum, harmonic components, and temporal correlations are especially critical for deriving individual cognitive signatures[5].

The fundamental steps involved in the processing of EEG signals are as follows:

- **Preprocessing:** Noise reduction and band-pass filtering (e.g., 2–15 Hz) to isolate cognitively relevant frequency bands
- **Segmentation**: Dividing the signal into specific time intervals to facilitate temporal analysis.
- **Feature Extraction**: Applying methods such as Power Spectral Density (PSD), Fourier Transform, Short-Time Fourier Transform (STFT), and Auto-regression to derive meaningful signal characteristics.
- **Dimensionality Reduction**: Utilizing techniques like Principal Component Analysis (PCA), t-Distributed Stochastic Neighbor Embedding (t-SNE), or tensor transformations to reduce data complexity while preserving salient information.
- **Classification**: SVM, KNN, CNN, Transformer-based network.

Through this architecture[6], EEG-based systems are capable of accurately characterizing individual cognitive traits and have become increasingly suitable for integration into human–machine interaction platforms.

BCI Systems and Mental Command Recognition

Brain–computer interfaces (BCIs) are innovative technologies that enable individuals to control external systems through neural activity. These systems have proven particularly effective in the rehabilitation of individuals with limited motor capabilities[7]. BCI systems typically rely on EEG data, from which signals corresponding to various mental states are extracted to perform distinct tasks.

Among the prominent paradigms employed in BCI systems are both endogenous and exogenous stimulus-based approaches, such as motor imagery (MI), steady-state visual evoked potentials (SSVEP), and P300. Numerous review studies have systematically highlighted the strengths of P300 and SSVEP paradigms in terms of signal processing, pattern recognition, and control techniques[8].

For individuals with complete loss of motor function, endogenous EEG-based BCI systems have been developed to enable online communication. These systems rely on paradigms that operate without the need for external stimuli. For instance, the feasibility of such systems has been demonstrated in a study utilizing a Riemannian geometry-based classification approach, which achieved an accuracy rate of 87.5%[9].

Within the scope of mental command systems, deep learning-based architectures have garnered significant attention in recent years. Comprehensive review studies evaluating the strengths and limitations of models such as (CNN), (RNN), (LSTM), (GAN), and Transformer have demonstrated that the integration of artificial intelligence into BCI applications substantially enhances overall system performance[10].

The applicability of BCI systems has been demonstrated not only in theory but also through practical implementations. For instance, by combining motor imagery and steady-state visual evoked potential (SSVEP) signals, a quadcopter was successfully navigated in three-dimensional space, achieving an accuracy rate of 87.09% using eight distinct EEG-based commands. Supported by real-time feedback and offline optimization, this system offers a high level of control capability based on mental commands within the domain of human–machine interaction. [8].

Morever, EEG-based BCI applications have also gained importance for elderly and disabled individuals, enabling the classification of various mental tasks through the application of machine learning techniques such as (ANN), (SVM) and (LDA) to EEG data.[11] .

EEG Based Applications in Human-Machine Interaction

Electroencephalography (EEG) signals are increasingly being utilized not only for medical diagnostics but also in systems that enable real-time human–machine interaction. EEG-based interfaces developed to enhance the quality of life for individuals with physical disabilities offer practical solutions in various application areas, including wheelchair control, robotic arm manipulation (as illustrated in Figure 2), and virtual keyboard usage[3].

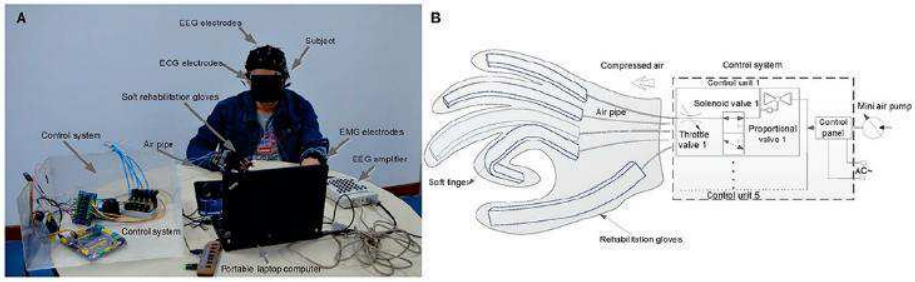


Figure 2. (A) The prototype BCI model and its experimental setup; (B) the control scheme of

the soft robotic hand. [3].

These systems are generally designed to control various devices through mental commands; for instance, directives such as 'move forward,' 'stop,' or 'turn right' are typically derived from paradigms like motor imagery or P300.[8] . In P300-based systems in particular, users are presented with a series of letters, icons, or options, and the system generates the intended output based on the user's attentional response to the selected item. This method has even made it possible for individuals with communication impairments to compose text by selecting letters[12,13].

The literature includes successful examples of controlling drones or robotic platforms using EEG signals. Notably, in a study developed for quadcopter control, motor imagery and steady-state visual evoked potential (SSVEP) signals were combined to enable three-dimensional movement, and the system achieved a command recognition accuracy of 87.09% [8]. In such applications, the system's real-time response latency and its ability to provide user feedback enhance the immediacy of interaction and significantly improve the overall user experience.

Another notable application area involves brainwave-driven robotic control systems. In these systems, EEG signals acquired from the user are preprocessed and classified—often using classifiers such as Artificial Neural Networks (ANN) and Support Vector Machines (SVM)—to enable directional commands such as forward, backward, or turning movements. In this context, the developed systems have demonstrated average classification accuracies exceeding 75%.[3]

In recent years, EEG-based interfaces integrated with virtual reality (VR) and augmented reality (AR) environments have also shown significant development. In such systems, EEG signals are used to adapt the virtual content based on the user's level of attention or emotional state. For instance, when focus levels decline, the content on the screen may be slowed down, or the brightness of the environment may be reduced. As a result, these systems enable not only command recognition but also emotion-driven interaction.[14]

In conclusion, EEG-based human–machine interaction encompasses a wide range of applications, from rehabilitation technologies and cognitive gaming to industrial machine control and autonomous systems. The ability to interpret user-derived signals with low latency and high accuracy is a critical factor that directly influences the reliability of these systems.

METHODOLOGY

In this study, the EEG-based mental command recognition system (Figure 3.) comprises three main technical stages: preprocessing, feature extraction, and classification. Each stage has been optimized using AI-driven methods to ensure effective noise reduction, transformation of signals into meaningful representations, and accurate classification

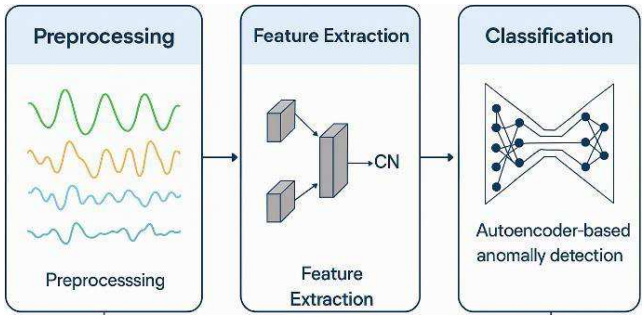


Figure 3. Method and system architecture

Preprocessing

Raw EEG signals, due to their high levels of artifacts—such as eye blinks and muscle movements—are initially subjected to filtering techniques. A band-pass filter (1–15 Hz) is applied to retain only the cognitively relevant frequency bands. Subsequently, the signals are segmented into fixed time windows to facilitate consistent temporal analysis[15]. This structure has been implemented to enhance the consistency of time-based analyses.

Feature Extraction

Instead of traditional hand-crafted feature engineering, deep learning architectures have been employed for automatic feature extraction. Convolutional Neural Networks (CNNs) have proven effective in capturing both temporal and spatial features. The model directly processes multi-channel EEG data as input and automatically learns task-relevant patterns through its convolutional layers.[16]. Thus, user-specific EEG signatures are modeled.

Classification

Both traditional and AI-based deep learning approaches have been utilized for the classification of EEG signals. Classical methods such as Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Linear Discriminant Analysis (LDA) have been preferred due to their low computational cost. On the deep learning side, architectures like Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and Autoencoders have stood out for their ability to capture complex patterns in time-series data. In particular, Autoencoder-based anomaly detection has emerged as a robust alternative for handling inter-subject variability, owing to its capacity to operate on unlabeled data.[17].

In conclusion, the system filters and segments the EEG data, learns spatio-temporal features using a CNN architecture, and evaluates the extracted representations through an Autoencoder-based classifier. As a result, it achieves high-accuracy mental command recognition with minimal noise interference.

DISCUSSION

The prominent methods highlighted in the reviewed studies are shaped around various deep learning architectures, classical machine learning classifiers, and hybrid feature extraction approaches. For example, in imagined speech classification, an approach in which phase-amplitude components derived using the Hilbert transform are processed through a CNN architecture has shown success in word-based command recognition; however, due to the complexity of the model, it has remained limited in real-time applications.[15].

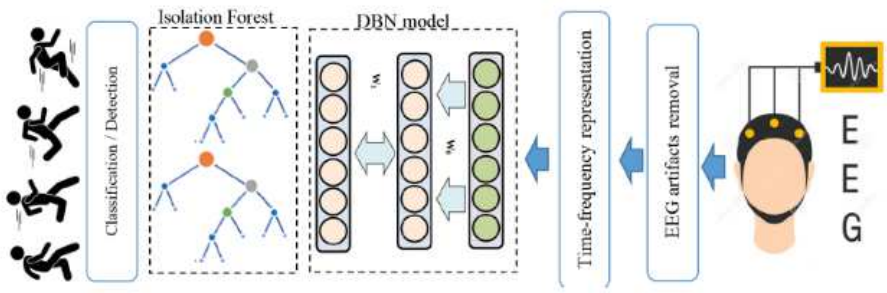


Figure 4. Schematic representation of general deep learning frameworks for tasking EEG-based mental discriminations [17].

In another study focused on mental task classification (see Figure 4), an autoencoder-based anomaly detection approach was proposed. In this model, only 'normal' task patterns were learned without relying on labeled data, and during the testing phase, task differentiation was performed based on reconstruction error[17].

Comprehensive reviews have compared CNN, RNN, LSTM, GAN, and Transformer architectures in detail. It has been reported that CNNs perform well in capturing spatial patterns, LSTMs are effective for temporal dynamics, and GANs are successfully utilized for data augmentation purposes[10].

Numerous studies have emphasized the importance of task-specific architecture pairings: for instance, the CNN+LSTM combination has been favored in motor imagery tasks, while Autoencoder-based structures have been preferred for attention-related tasks. In terms of accuracy, FAWT+ensemble models have demonstrated notable performance, reaching up to 97.8%. A comparative overview is provided in Table 1.

Study / Method	Application Area	Architectural	Accuracy percentage (%)
Hilbert + CNN	imagined speech	Deep CNN	-
Autoencoder	Mental task	Anomaly detection (CNN)	-
FAWT + IMV	Three classes of mental tasks	Ensemble + Wavelet	97.8
ANN & SVM	Motor task	Levenberg-Marquardt, RBF	98–99+
CNN + LSTM	Motor imagery	Hybrid Deep Learing	>94

Table 1. Mental Command Classification – Comparison of Methods

In line with the aforementioned reviews, this study has addressed the structure of EEG-based mental command recognition systems, the artificial intelligence methods employed, and their application potential. The reviewed literature demonstrates that both classical approaches (SVM, ANN, LDA) and deep learning-based methods (CNN, LSTM, Autoencoder) yield high accuracy in mental task classification.

Building on the studies discussed in the literature, this paper presents a practical application of EEG-based mental command recognition systems in the form of a BCI-assisted exoskeleton. Figure 5 illustrates a conceptual example of the proposed mechanical design. Prior research has demonstrated that EEG signals can be used to achieve upper and lower limb control through paradigms such as motor imagery (MI), P300, and SSVEP. The proposed project is specifically structured to support the rehabilitation of individuals with paralysis, with the aim of enabling lower-limb movement control through the exoskeleton.

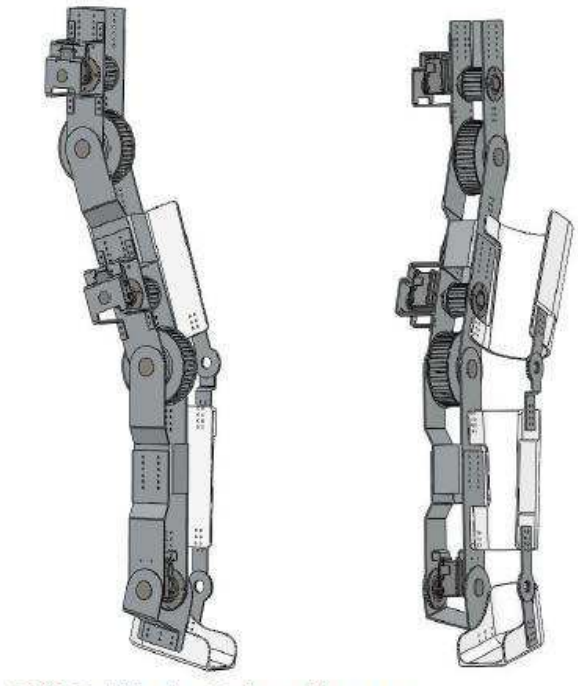


Figure 5. Conceptual solid model of the lower-limb exoskeleton system[18]

The proposed system is examined under two main categories;

i. **System Architecture**

- **EEG-Based Command Detection Unit:** This unit detects the user's motor imagery-based mental commands (e.g., "walk," "stop," "take a step") by recording data acquired from EEG electrodes.

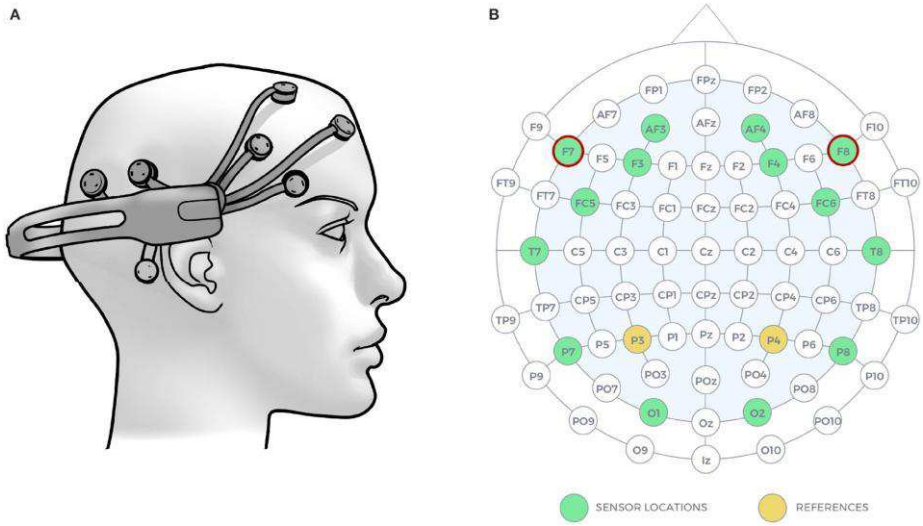


Figure 6. (A) (A) Emotiv EPOC+ headset was used for recording of brain activity, (B) the EEG signals were collected form 14 electrode sites (shown with green) according to the 10-20 system. The two electrodes with red circles were used for computation of Frontal Brain Asymmetry. (The images are taken from the documentation of the Emotiv EPOC+ helmet available at https://www.emotiv.com.)[19]

- **Feature Extraction and Classification Module:** Wavelet transform and adaptive autoregressive models can be employed for time-frequency analysis and obtaining clean signals. Signal classification can be performed using methods such as CNN or SVM. In

advanced models, deep learning-based hybrid architectures (e.g., CNN combined with LSTM) are also recommended.

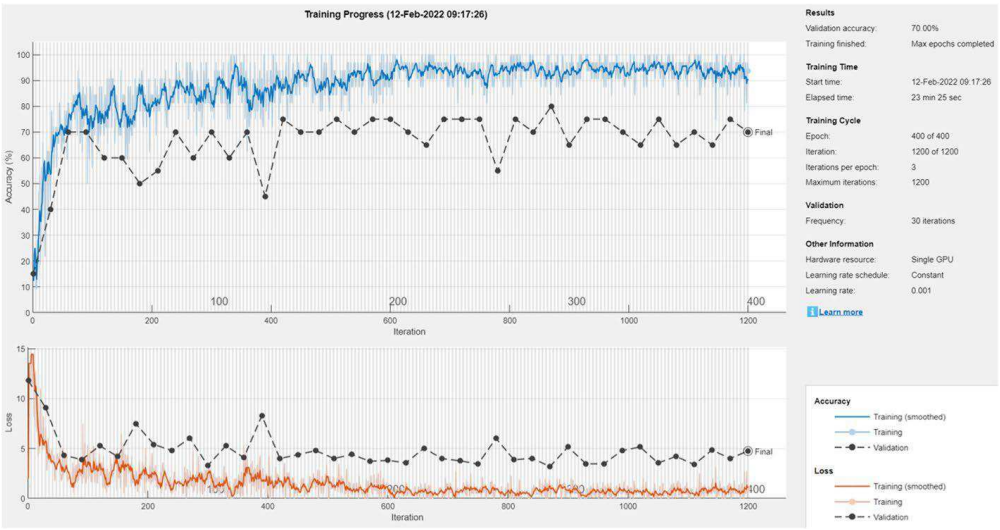


Figure 6. Example convergence curve for the proposed CNN architecture[15]

- **Motor Control Unit:** The detected commands are transmitted to the movement mechanisms of the exoskeleton. It is designed to provide appropriate and flexible rotational capabilities to the knee, hip, and ankle joints through linear actuators and servo motors. This control structure performs functions such as stepping, knee bending, or stopping based on user commands. **Feedback Mechanism:** In advanced models, visual or haptic feedback is provided to the user to stimulate brain–nerve plasticity. This setup enables a closed-loop rehabilitation system.

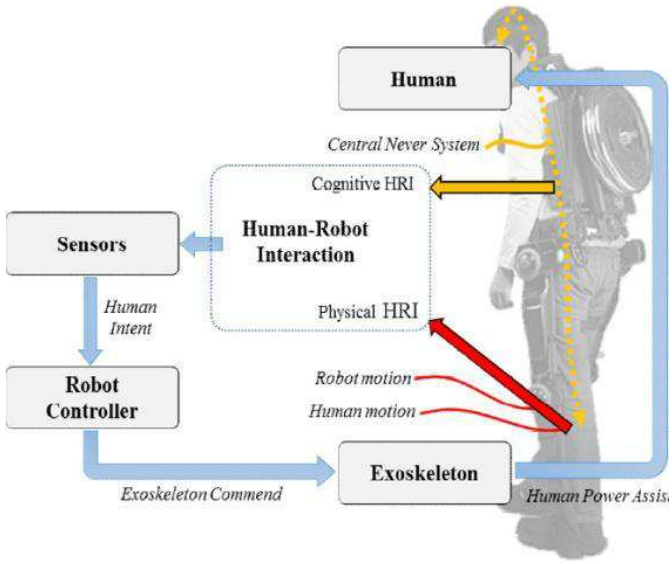


Figure 7. Conceptual Design of a Basic Exoskeleton Type [20]

ii. Paradigm and Signal Usage

The system is planned to be based on motor imagery (MI) or steady-state visually evoked potential (SSVEP) paradigms. When the user mentally attempts to move the right or left leg, this induces event-related desynchronization (ERD) in the alpha (8–13 Hz) and beta (13–30 Hz) waves of the motor cortex. These patterns are recognized by the system and converted into

corresponding commands. Alternatively, exogenous stimulus-based paradigms such as P300 can also be presented to the user.

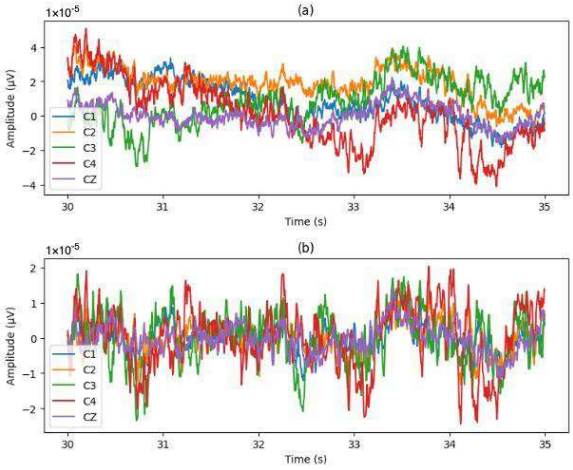


Figure 8. EEG signals from electrodes C3, C1, CZ, C2 and C4. The first 5 seconds of Subject 1 are displayed. (a) Raw EEG signal and (b) processed EEG signal

CONCLUSION

In conclusion, this study presents an EEG-based mental command recognition system as a fundamental component aimed at designing a system to support the rehabilitation of individuals experiencing motor impairments such as stroke. In recent years, the integration of BCI systems with robotic exoskeletons has established an effective closed-loop rehabilitation environment that facilitates the recovery of motor functions. In this context, real-time feedback mechanisms and user-specific model adaptations have become critical components for the system's usability and effectiveness. Moreover, the real-time processing of non-invasive EEG signals and their compatibility with low-power embedded platforms demonstrate the feasibility of portable, cost-effective, and scalable rehabilitation solutions.

Future studies should focus on improving inter-subject generalization capabilities, reducing inter-session signal variability, and validating these systems with larger-scale clinical trials. Once these challenges are overcome, EEG-based BCI systems have the potential to become practical and reliable assistive technologies for individuals with neuromuscular disorders.

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