IoT-Enabled Humanoid Robotic Arm Operated via Neural Signals and Eye-Tracking with Blink-Based Morse Communication

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Abstract

Amputations and neurologic disorders considerably restrict individuals' interaction with the environment. As per the WHO (2021), more than 30 million individuals are living with limb loss, and arm amputations account for the most prevalent. Existing BCI humanoid arms are still mostly restricted to the lab; invasive BCIs need brain surgery, whereas non-invasive EEG methods typically require multiple electrodes because of signal attenuation.

This work suggests an effective EEG-controlled humanoid arm system by employing six specific electrodes from a 32-channel data set (10–20 standard). It consists of three phases: signal preprocessing (band-pass filtering, CSP, and CWT), feature extraction by a pretrained VGG1c network, and classification to control the robotic arm. A LabVIEW GUI is used to control the arm's kinematics and dynamics.

Experimental testing scored S0.2% accuracy in classification, allowing for consistent and naturalistic arm control. These outcomes demonstrate the promise of non-invasive BCIs to improve independence and quality of life in amputees

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Keywords— Brain–Computer Interface (BCI); Electroencephalography (EEG); Common Spatial Pattern CSP, *humanoid arm,* Assistive Robotics.

Introduction

Brain–Computer Interface (BCI) technology was long thought to be purely speculative, but it has developed into a field of research and development with far- reaching applications in assistive technology. BCIs operate by taking neural signals from the human brain to perform beyond electronic devices, offering potential treatments for the physically disabled. The human brain has nearly 100 billion neurons and can be explained as an extremely advanced computational system. Of particular interest to BCI research is the cerebral cortex, which controls planning, “Pattern recognition and control of movement in the human brain are primarily governed by its four lobes: frontal, parietal, temporal, and occipital [1]. Among the various Brain–Computer Interface (BCI) modalities, electroencephalography (EEG) is the most widely adopted due to its non-invasiveness, high temporal resolution, and ability to capture real-time neural activity (EEG) has been used most extensively since it is non- invasive, has good temporal resolution, is portable, and costs moderately.

EEG-based BCIs categorize user intention from electrical brain activities and map them into control commands for other devices such as prosthetic limbs. However, EEG signals are highly non-stationary and prone to inter-session variability, making accurate classification and control difficult. Also, EEG signals normally consist of artefacts caused by external (e.g., power line interference) and internal (e.g., blinks, heartbeat, and muscle activity) motivations, which also complicate signal analysis [2]. Preprocessing and feature extraction techniques such as band-pass filtering, Common Spatial Pattern (CSP), and wavelet transformations are used to overcome these issues. Noise-resistant feature extraction is achieved through frequency- domain analysis, particularly using the Continuous Waveton Transform (CWT), by transforming 1D EEG signals to a 2D frequency–time domain (scalograms). By emphasizing EEG activity from motor cortex electrodes (C3, Cz, C4) and parietal electrodes (P3, Pz, P4), these techniques enhance the accuracy of motor imagery signal classification. In recent years, feasibility has also been demonstrated in combining these feature extraction methods with deep learning models towards decoding of motor signals. This has enabled real-time control of prosthetic limbs and, in addition, proved the feasibility of BCI systems towards rehabilitation and assistive technology.

Based on these developments, in this study, a new approach to EEG-based feature extraction and classification with a pretrained convolutional neural network (VGG16) is presented to operate a robotic prosthetic arm with greater precision and responsiveness.

Literature Review

A. Processing EEG Signals

Grasp-and-Lift EEG Dataset was designed to research the interaction of human and brain-computer interface (BCI) devices for welfare, EEG signals and movement. The data was recorded with the AntiCap of patients with neurological disability with 32 electrodes arranged according to the 10–20 system, EEG recording system 12 healthy participants each performed multiple grasp-and .and sampled at 500 Hz, Contact forces. lift trials with hand and object motion monitored by 3D sensors raw, to improve accuracy and kinematics were used to get event labels, torques signals were filtered using Savitzky-Golay filtering.

B. Channel Selection

EEG signals corresponding to motor activity are primarily localized near the C3, C4, and Cz channels (motor cortex) and P3, P4, Pz channels (parietal lobe – thinking).

These six channels were chosen as they transmit maximum motor-think information for grasp-and-lift tasks.

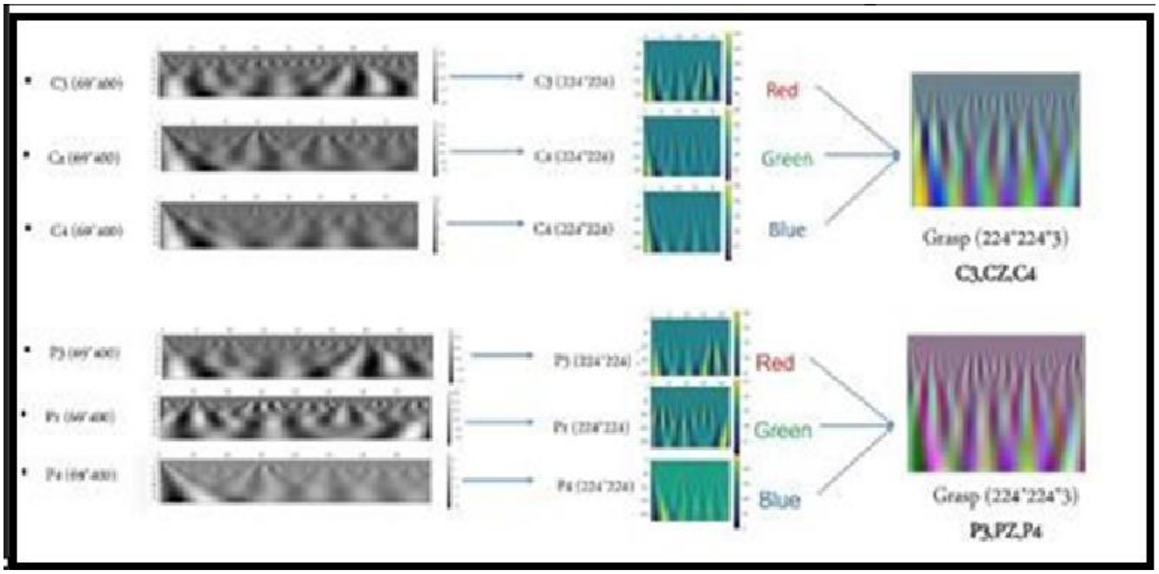

Figure 1: *Chosen EEG electrodes (C3, C4, Cz, P3, P4, Pz) shown on the 10–20 map.*

C. Filtering and Normalization

The EEG signals were band-passed between 7–30 Hz to demote μ and β rhythms, removing artefacts caused by heartbeat (<1.2 Hz), eye blink (<4 Hz), and muscle noise (>30 Hz). After filtering, Common Spatial Pattern (CSP) was used for improving class separability. As a final step, normalization of the data was performed by subtracting the mean and dividing by the standard deviation.

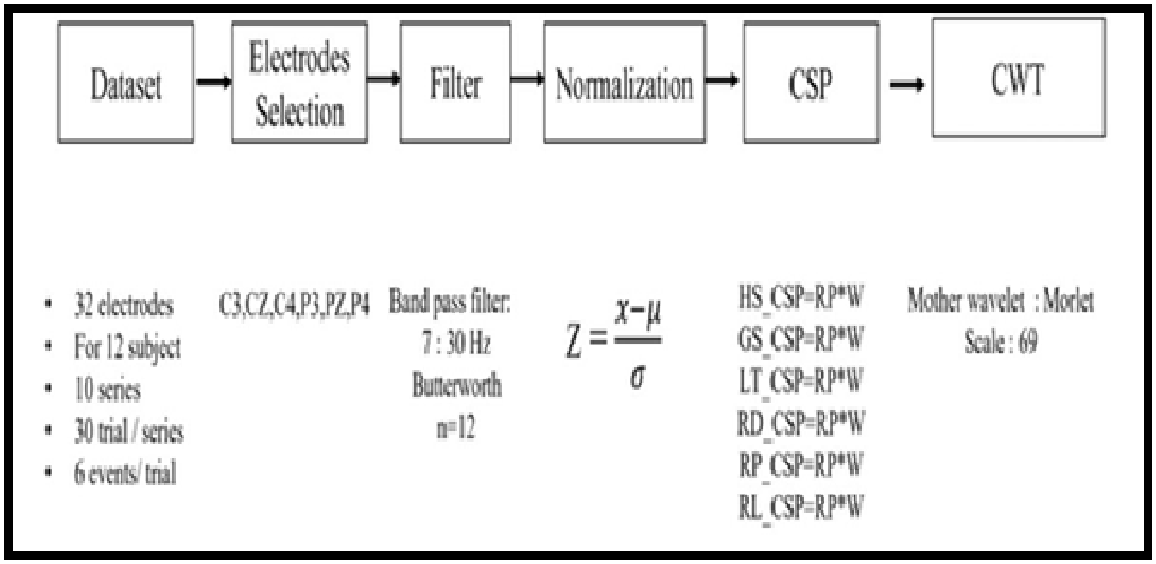

Figure 2: *EEG preprocessing (Filtering → CSP → Normalization).*

D. Continuous Wavelet Transformation (CWT)

The filtered EEG signals were converted to scalograms using Continuous Wavelet Transform (CWT). In contrast to Fourier transforms, wavelet transforms offer improved time-frequency resolution. The scalograms (69×400) were resized to 224×224 pixels using bicubic interpolation to match the VGG16 CNN model.

E. Pre-Trained Network (VGG16)

The VGG16 convolutional neural network was utilized as it has strong feature extraction power. Initially trained on ImageNet (14 million images, 1000 classes), it exhibits high accuracy and can transfer learned features (edges, patterns, textures) well into EEG-based image inputs. Input scalograms were applied into VGG16 for motor intention classification.

F. Mechatronic System

The mechatronic implementation combines the neural output with actuation. The prosthetic arm is a 2 DOF planar robot arm, constructed with PLA material via 3D printing, of weight 2.25 kg and length of ~80 cm. It has hand, forearm, biceps, and shoulder modules, providing natural functions such as reaching, grasping, and handshakes.

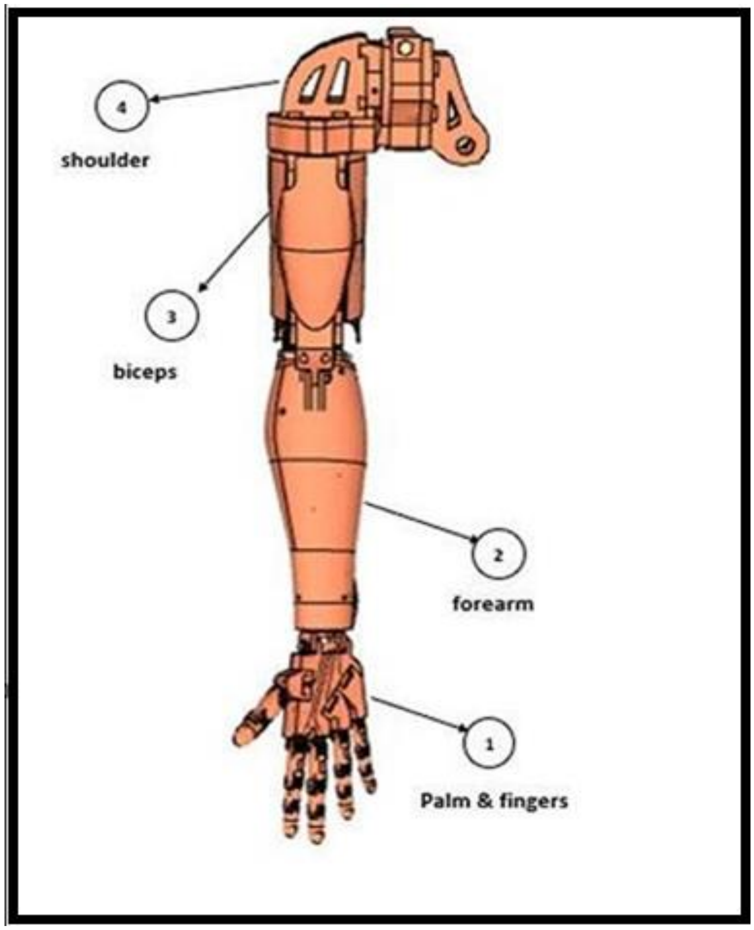

Figure 3: *3D-printed humanoid arm structure (mechanical components).*

G. Kinematics and Dynamics

Forward kinematics calculates the orientation and position of the prosthetic arm, while dynamics calculate forces and accelerations during motion. Transformation matrices involved the Denavit-Hartenberg (D-H) convention, and motion equations used Lagrangian dynamics.

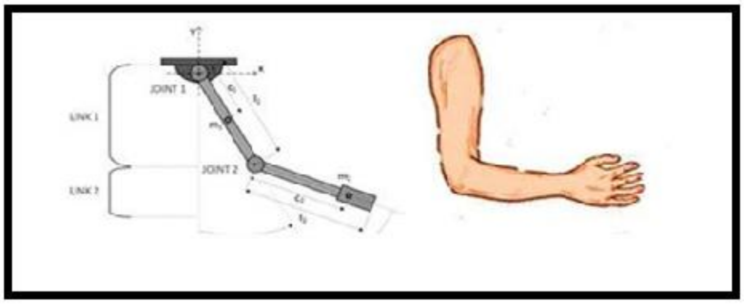

Figure 4: *Force/dynamic analysis diagram of humanoid arm*

System Design and Methodology

Hardware Components

- Neuro-Signal Acquisition: EMG sensors (MyoWare/ADS1299), optional EEG headset (OpenBCI, Muse).
- Control Unit: ESP32 microcontroller for signal processing and Wi-Fi connectivity and eye-tracking and blink detection.
- Robotic Arm: 3D-printed humanoid arm with slime servo motors (SG90, MG996R, ES3301) for fingers and larger joints.
- Eye-Tracking Module: IR-based camera with OpenCV for gaze tracking.
- Power System: 12V LiPo battery and regulated DC supply.
- IoT Integration: Cloud-based dashboard using Firebase/AWS IoT for remote monitoring.

Software Components

- Signal Processing: EMG signals filtered and classified to map muscle activity to arm movements.
- Motor Control: PWM-based control algorithms for servo and stepper motors.
- Eye Tracking: OpenCV algorithms for gaze estimation and object targeting.
- Morse Code Translator: Blink detection with timing thresholds mapped to dot/dash patterns and converted to text.
- IoT Dashboard: Real-time monitoring of signals, arm status, and communication outputs.

Results and Analysis (Planned)

The system will be tested in the following areas:

- Accuracy of EMG signal classification: Predicted >85% using training sets.
- Latency in robotic arm response: Goal <150 ms for real-time.
- Eye-tracking accuracy: ±1–2° error in estimating gaze.
- Morse code detection rate: >90% for trained individuals.
- IoT dashboard performance: Real-time visualization of data with <300 ms delay.

These performance metrics are based on benchmarks from similar systems and will be validated through prototype testing.

Applications

- Assistive Technology: Prosthetic control and communication for disabled individuals, especially patients with severe neuromuscular impairments
- Medical Rehabilitation: Neurofeedback and motor rehabilitation for stroke or injury patients
- Military Defense: Remote-controlled robotic arms for hazardous environments, bomb disposal, and surveillance.
- Industrial Automation: Precision handling of delicate or hazardous materials.
- Research: Human–machine interaction studies and experimental neuroprosthetic systems.

Conclusion and Future Scope

This research presents a novel integration of neuro-control, eye-tracking, and Morse code Communication into a humanoid robotic arm, making it an advanced assistance and automation system. The proposed design addresses the limitations of existing prosthetics by introducing IoT-enabled control, multi-modal interaction, and affordable implementation.

Future work will focus on:

- Full EEG-based brain–computer interface integration for thought-controlled movements.
- Haptic feedback systems enable tactile sensing.
- Advanced AI-driven adaptive grip mechanisms.
- Cloud-based teleoperation and data-driven learning for medical and industrial applications.

This research contributes to the growing body of work in neuro-controlled robotics and has significant potential for commercialization in healthcare, defense, and industrial automation.

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