



Neuro-Muscular Interface Based Bionic Arm Using EEG and EMG Signals

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Abstract: Advanced prosthetic limbs, or bionic arms, may be seen as the best achievement in biomedical engineering. The design of the prosthetic arms not only seeks to take the place of an amputated or lost arm, but is able to often mimic complex functions in naturally functioning arms, and restore a large amount of functionality. Recent advances in technology are generally providing improved functionality and control, and creating a better overall user experience with a bionic arm. Recent dramatic advances in the prosthetic limbs industry have pioneered extensive bionic limb capabilities and the experiences of natural functionality in our interactions with the environment as if it were a naturally occurring limb. Recent advances in bionic arms have made substantial strides in accessing human potential and prosthetic limbs, enhancing sensory feedback, improving neural integration, and implementing intuitive control using muscle implants and brain machine interfaces.

Index Terms - Bionic arm, Brain-Machine Interface, Neurological Integration, Prosthetic Limb, Sensory Feedback

1. INTRODUCTION

Bionic arms are an example of advanced prosthetic devices that are controlled using electronic components to mimic natural arm movements [1]. Traditional prosthetic devices do not provide the finesse or quick response time needed to perform complicated tasks using the prosthesis. For amputees, neuro-muscular control using EMG sensors and EEG sensors provide the ability to control the arm based on their muscle signals or brain activity [2, 3]. These type of systems will benefit amputees by enhancing mobility, independence, and quality of life.

Both EEG and EMG are instrumental in enabling intuitive control of a prosthetic limb. EMG sensors will read the signals that electrical activity produces from the muscles, for example, the prosthetic could respond in space similar to natural muscle without requiring either additional muscle activity or performance of a deliberate action. EEG will read the subject's brain signals, providing a method of controlling the prosthesis when using muscle activity to control the device is not possible [4, 5]. EMG and EEG combined provide a high degree of accuracy and responsiveness in real-time for prosthetic function [6]. In general, this will make the control or usage more usable for the user, and the user will have increased confidence in the bionic device to perform the functions or tasks that they need to perform.

This primary goal of this study is to establish a bionic arm controlled by neuro-muscular signals, particularly EEG and EMG, for more life-like movement represented in real-time. It aims to improve the control of prosthetic limbs in these areas - bionic limbs should enhance the user's life. And, it is also our goal to make it affordable and accessible for amputees wherever they are in the world. This paper presents an innovative approach by using EMG and EEG signals for dual-mode control of the bionic arm. The system has further reduced the overall cost through open hardware components and other accessible resources sourceable to evaluate cutting edge prosthetics, all-the-while improving the accuracy and responsiveness of the device as

compared to traditional single-input prosthetic limbs. This research extends the field of make neuro-prosthetic limb technology more intuitive and user-friendly.

2. BACKGROUND OF THE PRESENT STUDY

Prior research on prosthetic control systems has mainly focused on EMG or EEG signals in isolation. EMG based systems have been shown to provide reliable sources of information about muscle activity for controlling primitive movements of prosthetic limbs [7]. EEG based systems are generally more complicated, however they have successfully demonstrated hands-free control using brain signals. It should also be noted that many authors faced problems with accuracy of movement, noise, and anthropometric differences among users [8-10]. Very few studies have explored the use of EEG and EMG together for improved and more intuitive prosthetic control. User convenience is an important aspect and uni-modal systems provide this with EMG or EEG based systems giving both strengths and weaknesses to performance depending on the movement required while the user is remaining [11]. EMG systems produce response times that are faster than EEG signals, however it is reliant on the effort of the muscle and not always available for some users due to strength. EEG signals produce hands-free control of the prosthesis, autonomously adapting to user commands, but in general can be noisy and much slower in processing time than EMG [12]. Multi-modal systems have offered users the advantages of both source of information adding reliability, precision, and adaptability. This fusion allows for more intuitive and versatile prosthetic control for an even wider variety of users. Currently, research has tended to focus on either EEG or EMG models separately, reducing the impact of hybrid model control [13, 14]. Many systems do not accommodate real-time variability and are susceptible to noise interference in real-world settings. Since advanced prosthetics are costly and require complex setups, many users and subjects may never benefit from or experience advanced systems. Also, there isn't a lot of work that combines EEG and EMG commercially successfully into a user-friendly, portable design. These gaps create opportunities for inexpensive multi modal and responsive bionic control systems.

3. SYSTEM ARCHITECTURE AND DESIGN

This project involves the design and development of a bionic arm system that utilizes a neuro-muscular interface running on EEG (Electroencephalogram) and EMG (Electromyogram) signals. The architecture consists of interfacing brain and muscle signal acquisition modules, signal preprocessing, feature extraction, and machine learning-based classification of the user's intent. The EEG signals capture a motor imagery or cognitive intent, while the EMG signals provide muscle activity during fine-control of the arm. The processed EEG and EMG signals drive the actuators on the prosthetic arm, allowing for natural, real-time movement. This system will enhance the ability to restore motor function for individuals who are amputees or have neuromuscular disorders, through the use of an intuitive brain-machine-interface. The flow diagram of overall system is depicted in Figure-1.

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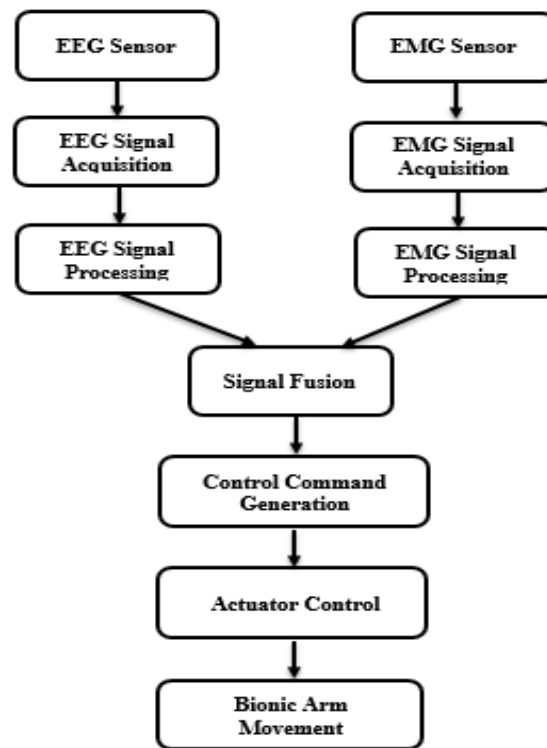


Figure-3.1: Flow Diagram of Signal Acquisition & Processing for Bionic Arm Movement

Entire experimental set up (Figure-2) is divided into two main parts such as

i) Signal Acquisition and Processing

a) EEG signal acquisition: electrode placement, preprocessing (filtering, artifact removal).

EEG signals can be measured by positioning electrodes on points along the scalp. The electrodes are usually placed over a region of the skull related to the body's motor activity- this is how users can control a prosthetic. The signals are then amplified (in order to pick up the weak body electrical activity) and sent to a processing unit. Preprocessing involves filtering out electrical noise caused by electrical components such as power lines or movement of the body. After preprocessing comes the use of artifact removal strategies such as independent component analysis (ICA)

b) EMG signal acquisition: muscle selection, noise reduction.

EMG signal acquisition begins with selecting muscles that control the intended movements, typically in the forearm or upper arm. Electrodes such as the MyoWare EMG sensor are then placed over the muscles to collect electrical activity upon contraction. Noise reduction (e.g., high-pass filtering to get rid of lower frequency noise) is applied during processing to eliminate the lower frequency noise from relevant data. In addition, noise from the muscles was reduced by placing the electrodes on the muscle and amplifying the signal. The processed EMG signal is then used to control the movements of the prosthetic arm following their respective target motions.

c) Feature extraction techniques (e.g., FFT, RMS, MAV).

Feature extraction methods are employed to transform raw EEG and EMG signals into useful information for controlling prostheses. The FFT (Fast Fourier Transform) extracts meaningful information based on the frequency content of the raw signal, and is important for identifying unique actions via brain or muscle activity. The RMS (Root Mean Square) feature represents the energy of the signal, which may later relate to intensity of contraction. The MAV (Mean Absolute Value) feature describes the overall amplitude of the EMG signal to determine muscle activation.

d) Classification algorithms (e.g., SVM, ANN, k-NN) or control logic.

Classification algorithms classify and interpret the acquired features of EEG and EMG signals to control the prosthetic arm. SVM (Support Vector Machine) is helpful in distinguishing between different muscle or brain states with identified patterns. ANNs (Artificial Neural Networks) are capable of learning complex relationships and with each identification this can improve accuracy over time. k-NN (k-Nearest Neighbors) looks at the identified signal and classifies it with a label similar to training data for quick alternatives. The classification algorithms help inform the control logic to convert the identified signals into discrete motor commands processed to be executed by the bionic arm.

ii) Control Strategy and Implementation**a) Fusion of EEG and EMG data for control.**

The combination of EEG and EMG data brings together both brain and muscular signals to facilitate control of prosthetic limbs. The use of EEG and EMG signals together expands the possibilities in terms of providing more precise, intuitive movements while capitalizing on the strengths of both modalities. The EEG signals provide a brain-based control signal and the EMG signals provide muscle-based input that allows for faster and more responsive movements. The data fusion (surface EMG and EEG) techniques used in the control of a bionic limb consist of weighted averages or machine learning models to account for the EEG and EMG signals in one seamless control interface. The multi-modal approach can enable more complex adaptive and precise actions with the bionic arm.

b) Decision-making model (e.g., majority voting, confidence-weighted).

A solid decision-making model is essential for interpreting combined EEG and EMG signals to effectively control a prosthetic arm. The majority voting method focuses on picking the most common or dominant signal classification from various modalities or time frames, which helps ensure reliable control. Confidence-weighted models take it a step further by assigning different importance levels to each signal based on how reliable they are, allowing for more precise control when certain signals are stronger or clearer. These models play a key role in resolving conflicting data and enhancing the system's responsiveness. By using these decision-making strategies, the movements of the prosthetic arm can become smoother and more in tune with the user's intentions.

c) Control algorithm for arm movement (e.g., rule-based, model predictive).

A control algorithm for arm movement takes processed EEG and EMG signals and turns them into precise motor commands. Rule-based algorithms rely on set conditions to trigger specific actions, like flexing the arm or opening the hand, based on muscle or brain activity. Model predictive control (MPC) looks ahead by analyzing past signal data, optimizing the arm's trajectory for smoother and more natural movements. Both methods aim to enhance the accuracy and responsiveness of the prosthetic. The choice of algorithm hinges on how complex and adaptable the user's needs are.

For real-time implementation, it's crucial to process EEG and EMG signals quickly to ensure the prosthetic arm responds immediately. The sensors continuously sample signals and send them to the microcontroller or processing unit. Feature extraction and classification happen in real-time, allowing the system to decode what the user intends right away. The control algorithm then processes these classifications and sends motor commands to the actuators. To keep latency to a minimum, the entire system is fine-tuned for fast processing speeds, ensuring smooth and responsive arm movements.



Figure- 3.2: Experimental Set up

4. RESULTS AND DISCUSSION

Quantitative results are essential to evaluate the effectiveness of the prosthetic control system. Signal classification accuracy measures how accurately the system interprets EEG and EMG signals, often achieving accuracy rates above 90% in well-calibrated systems. Response time refers to the delay between signal detection and motor response, typically aiming for a sub-100ms latency for smooth, real-time control. Additional metrics may include motion precision for specific gestures and adaptive learning performance over time. These results demonstrate the system's reliability, responsiveness, and ability to meet user expectations.

Functional outcomes measure the success rate of performing specific tasks with the prosthetic arm. Tasks such as grasping, lifting, or pointing are evaluated to determine how effectively the system translates user intent into action. A high success rate indicates that the prosthetic can perform complex movements reliably and with minimal error. Functional outcomes also assess the user's ability to adapt and control the prosthetic over time. These outcomes help gauge the practical benefits of the system, including improved independence and quality of life for the user.

Comparison with existing systems highlights the advantages and limitations of the proposed prosthetic control method. Many current systems rely solely on EMG or EEG, offering limited control or responsiveness. In contrast, integrating both EEG and EMG signals allows for more intuitive and precise control of the prosthetic. Existing systems often struggle with high costs, complexity, and accuracy, whereas the proposed approach focuses on affordability, real-time performance, and ease of use. This multi-modal integration provides a significant step forward in enhancing prosthetic functionality and user experience.

One limitation of the current system is its reliance on accurate signal acquisition, which can be affected by noise or poor electrode placement. Additionally, the control algorithms may struggle with complex, dynamic movements in real-world environments. Another challenge is the need for continuous calibration to maintain optimal performance. Future improvements could include more robust noise filtering techniques, adaptive learning algorithms, and enhanced sensor technologies for better signal reliability. Incorporating AI-driven systems for real-time adjustment and personalization could further improve usability and performance.

5. Conclusion

The research has shown that by combining EEG and EMG signals, we can significantly improve the control of prosthetic limbs, creating a more intuitive experience for users. This integration allows for more precise and adaptable control, which translates to better performance in various tasks. The system boasts impressive classification accuracy and quick response times, making it ideal for real-time prosthetic applications. The findings indicate that fusing multiple signals can really boost the effectiveness of bionic arms across different situations.

This research has a profound impact on advancing the field of neuro-controlled prosthetics. By merging EEG and EMG signals, it enhances the accuracy, responsiveness, and overall intuitiveness of controlling prosthetic arms. Plus, the system is affordable and performs in real-time, making it accessible to a broader audience. It

also sets the stage for future breakthroughs in smart, adaptive prosthetic technologies. Ultimately, this work aims to improve the independence, functionality, and quality of life for those who have experienced limb loss.

Future directions for this research include integrating deep learning algorithms to improve the accuracy and adaptability of signal classification over time. The use of 3D printed limbs can reduce costs and allow for customizable prosthetic designs tailored to individual users. Incorporating haptic feedback will enable users to feel sensations like pressure or texture, making control more intuitive and immersive. Advancements in wireless communication and miniaturized electronics can further enhance portability and usability.

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