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STUDENT PAPER

REVOLUTIONIZING MOBILITY: BRAIN COMPUTER INTERFACES AND THEIR APPLICATIONS IN PROSTHETICS

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ABSTRACT

The revolutionary field of brain-computer interfaces (BCIs) and robotic prosthetics offers new hope for restoring independent movement for the disabled. By enabling direct communication between a person's brain signals and external machines, BCIs have demonstrated their ability to interpret brainwaves and execute intended movements. These technologies have empowered individuals who have been immobile for years to regain independence. BCIs have been used to perform tasks such as typing and accurately controlling prosthetics. Through practice and the application of machine learning, BCIs refine their ability to decode brainwave patterns and infer users' intentions. A significant challenge remains in implementing BCIs that can translate high-dimensional, real-time neural data into precise motor commands for prosthetic arms through risky surgery. Despite this, advancements in BCIs and robotic prosthetics hold tremendous potential to dramatically improve the lives of those who have lost the ability to move. The integration of BCIs with prosthetics gives amputees a deeper intuitive connection with their artificial limbs.

INTRODUCTION

Every year, thousands of people suffer from traumatic incidents that result in severe bodily damage, with over one million amputations happening globally every year (Pro Medical East 2023). This can lead to several negative implications on their mental health and severely impairs their daily functioning. Prosthetics have been used for centuries in the form of hook hands and wooden legs, but these substitutes don't provide much connection to the user and do not provide the same level of mobility as their previous limbs. Recent research suggests

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combining prosthetics with BCIs offers profound new possibilities for people who have lost their limbs. BCIs are a collection of technologies that translate the electrical signals from a brain's neural activity into instructions for an external computer or machine. A typical BCI system operates by first collecting neural information, secondly decoding it using an algorithm, and finally performing the intended action with an effector (Vilela and Hochberg 2020). To collect data from the brain, a BCI needs to collect the electrical signals produced by the brain's neural activity (Vidal *et al.* 2016). BCIs use electrodes to capture brain activity, with methods varying from non-invasive electroencephalography (EEG) to invasive electrocorticography (ECoG) each offering differing pros and cons (Choi *et al.* 2018).

EEG is when electrodes are placed onto a user's scalp and record neurological data (Tariq *et al.* 2018). EEG offers a non-invasive method to extract signals from a patient's brain, and is the most widely used because of its practicality, safety, and cost-effectiveness (Orban *et al.* 2022). The other mode of gathering data for BCIs is through electrocorticography, or ECoG (Shih *et al.* 2012). ECoG utilizes an array or grid of electrodes implanted intracranially into a brain. This allows for greater accuracy in data collection (Shih *et al.* 2012). These signals are collected and decoded with machine learning and complex algorithms to produce commands to be carried out by a robotic limb.

In this article, we will investigate different methods of BCI collection, processing and output. We will also look at the practical applications, challenges, implications for society, and the future that BCIs will help create.

BCI METHODS FOR PROSTHETIC CONTROL

There are many ways that BCIs and robotic limbs have been combined. Medical professionals have done this through EEG, ECoG, and intracranial implementations.

Through EEG, data is collected through electrodes placed on the scalp. EEG systems commonly use either wet electrodes, typically silver/silver chloride (Ag/AgCl), which require a conductive gel, or dry electrodes, which do not need gel but often face higher impedance issues (Al-Qahtani *et al.* 2024). There are a few problems with EEG however, as EEG signals are easily distorted through background noise, such as power lines (Shih *et al.* 2012). In general, the closer

the BCI is to the neurological tissue, the more effective it will be. Microcontrollers, including Arduino boards, receive movement commands and adjust motor parameters to control limb direction, speed, and position (Al-Qahtani *et al.* 2024). Alternatively, ECoG utilizes microelectrode arrays, which are tiny needle-like electrodes implanted directly into brain tissue (Raspopovic *et al.* 2014), specifically electrodes approximately 2.3 mm in diameter and 1 cm apart (Miller *et al.* 2020). The ECoG array collects the electrical potential summing from the individual neuron populations from each electrode this allows for greater accuracy in data collection (Miller *et al.* 2020). Using Bluetooth, this data can be transmitted to a computer, like an Arduino (Priya *et al.* 2025), which then interprets brainwave data to produce appropriate movement commands (Al-Qahtani *et al.* 2024).

When comparing EGG and ECoG, the ECoG offers more in terms of signal quality, data reliability, and long-term stability, but is more costly and at risk of surgical implications than the EEG. Several brain signals are utilized by both EEG and ECoG, including P300 EEGs and sensorimotor rhythms (SMRs) (Liu *et al.* 2022). But steady-state visually evoked potentials (SSVEPs), which are natural responses to visual stimuli at specific frequencies, are the preferred brain signal to use. SSVEPs are evoked in the brain when looking at certain objects that flicker at distinct frequencies (Liu *et al.* 2022), and they are the preferred brain wave to use due to their higher signal to noise ratio and the fact that there is no need for initial calibration or learning period for the users (Li *et al.* 2024). The brain responds to these flickers by generating electrical signals that can be detected through EEG. Motor imagery is then used to trigger the selection of a certain task. Signal processing algorithms are employed to decode user intentions from noisy neural data (Moreno-Calderon *et al.* 2023). The acquired signals are then processed using a series of algorithms to decode intentions, like moving a prosthetic limb (Lebedev and Nicolelis 2017). Specifically, EEG signals are processed using feature extraction (CSP – Common Spatial Patterns) and a classifier (QDA – Quadratic Discriminant Analysis) to classify different skills (Aggarwal and Chugh 2019).

Common Spatial Pattern (CSP) is a feature extraction technique widely used in BCIs. CSP provides spatial filters that optimally discriminate between two classes of EEG data in the least-squares sense, this capability translates to higher classification accuracy in motor imagery BCIs (Falzon *et al.* 2012). Channel contributions indicate the

areas of the brain responsible for certain motor imagery tasks, and the classifier then determines the user's choice. Next, this motor imagery is used to control movement. For example, the user imagines moving their hand right, and this is processed through feature extraction using a binary classifier. This determines whether a user is in a rest state or a "move" state and how the user wants to move.

Brain signals are subsequently translated into commands that control motors and actuators in prosthetic devices, allowing complex movements like gripping or fine motor adjustments (Vilela and Hochberg 2020).

APPLICATIONS IN PROSTHETICS

Prosthetics have made significant strides in restoring lost functionality, particularly in sensory feedback for amputees. In the realm of brain-computer interfaces (BCIs), companies like Neuralink are pushing the boundaries of what's possible with neural technology. These companies are working to enable individuals to control prosthetic devices simply by thinking about them, a significant leap toward seamless integration between the human brain and machines (Mullin 2024). Notably, there have been successful applications of BCIs in which paralyzed individuals were able to control robotic arms and gain a sense of touch in their prosthetics, offering hope for those who have lost both mobility and sensation (University of Calgary 2023). BCIs are also playing a crucial role in the development of motor neuroprosthetics. For amputees, electromyographic signals (EMG) from the peripheral nervous system are used to better connect the motor nerves in the residual limb to the prosthetic. This is achieved through surgery, which enhances the pairing between nerves and prosthetic components, resulting in more intuitive limb control (Cogan 2008). These advances ensure that prosthetics are not only functional but also capable of responding to the user's intentions in a more human-like manner.

In addition to prosthetic limbs, non-invasive applications of BCIs are gaining traction. EEG-controlled exosuits, for example, have been shown to assist paralyzed individuals in regaining some degree of mobility (Colucci *et al.* 2022). By interpreting brain signals via EEG, these exosuits can augment movement and assist with activities that would otherwise be impossible for someone with spinal cord injuries. This kind of technology shows promise in facilitating more natural

interactions between individuals and the environments around them, thus improving independence and quality of life.

CHALLENGES

One of the primary challenges related to BCIs is the risk associated with brain surgery, as implantation of electrodes involve invasive procedures that carry potential dangers. These risks include inflammation, tissue scarring, seizure, and hemorrhaging (Shih, Krusienski and Wolpaw 2012). Tissue damage due to surgical implantation can trigger immune responses, leading to inflammation and the formation of scar tissue, which can interfere with the BCI's functionality and cause further damage to the brain (Cogan 2008). Neuroplasticity–the brain's ability to reorganize and form new neural connections–may be altered over time if electrode implants disrupt natural neural pathways or induce changes in brain activity (Shih *et al.* 2012). On the technical side, BCIs face significant material and engineering challenges.

In addition, electrodes used in BCIs are exposed to a hostile environment in the brain, which can lead to corrosion, tissue encapsulation, or mechanical wear. This degradation reduces the quality of the signals detected by the electrodes, leading to a decline in the BCI's performance and necessitating replacement or recalibration of the devices. Additionally, maintaining stable electrical contact between electrodes and neurons in the dynamic environment of the brain is a persistent challenge. The brain's movement and natural shifts in position can disrupt the interface, leading to signal instability and the potential for data loss or misinterpretation (Soangra *et al.* 2023).

Thus, while significant progress has been made in recent years, ongoing research is required to address these biological and technical obstacles to make BCIs a viable and reliable solution for medical and other practical applications.

FUTURE POSSIBILITIES

Humans currently have limited ways of communicating information with devices, with a mouse and a keyboard. But with more BCI advancements, it may be possible to transmit thoughts into computers and have them decode brain signals so that computers can understand humans. Developments in neural engineering and artificial intelligence aim

to create seamless integration between prosthetic limbs and neural commands, improving both user experience and functionality (Lebedev and Nicolelis 2017). One area of growth is the implementation of advanced sensory feedback systems. Currently, most prosthetic devices lack the ability to replicate natural tactile sensations. Future innovations will focus on integrating haptic technologies that provide feedback on touch, pressure, and temperature. This advancement would not only allow users to better interact with their environment but also enhance motor control by enabling more precise grip and manipulation of objects (Kim *et al.* 2018).

The integration of wireless communication technologies will further enhance BCI-controlled prosthetics. Wireless systems enable the seamless transmission of neural commands to robotic limbs without physical connectors, reducing the potential for mechanical failures. Coupled with machine learning algorithms, these systems could adapt to user-specific neural patterns, anticipating intended movements and improving overall control (Shih *et al.* 2012). AI-driven adaptive features may even allow prosthetic devices to self-learn from the user's behavior, enhancing usability over time (Chopra and Emran 2024). Continuing these endeavors will pave the way for BCIs and prosthetics to improve lives meaningfully. Further connection with the human body and machine could break boundaries of what the human body can do.

CONCLUSIONS

Brain-Computer Interfaces (BCIs) and prosthetics offer unprecedented opportunities for enhancing human capabilities and improving quality of life. BCIs come in two primary forms: non-invasive EEG and invasive ECoG. These technologies enable the decoding of brain signals, such as Steady-State Visual Evoked Potentials (SSVEPs), to translate thoughts or intentions into action, offering restored movement and communication for those with severe disabilities. The potential societal implications of BCIs and prosthetics include restoring mobility and function to those with spinal cord injuries or amputations, to augmenting human cognitive or physical abilities for everyday tasks. However, several challenges accompany the development of these technologies. High costs, and safety concerns related to invasive procedures all require careful attention. Future advancements could lead to fully integrated systems that enhance brain function or lead to completely new forms

of human-computer interaction. In my view, BCIs and prosthetics are pivotal in overcoming limitations of physical or cognitive disabilities. Ultimately, BCIs are a developing area of biomedical science that give amputees to regain a feeling that they have lost, autonomous mobility, in a way they never have before.

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