Machine Learning and Brain Computer Interfaces

Impact of BCI-Integrated Prosthetics

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On my honor as a University student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments.

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Introduction

Brain computer interfaces currently require extensive user training in order to effectively isolate and translate the desired brain signal characteristics into desired control signals for external devices. Machine learning algorithms allow for computers to generalize data and identify trends to perform tasks without explicit instructions. In my Technical Report, I will discuss the possibility of using machine learning algorithms to significantly reduce the amount of effort required by the user to build a mapping from their brain activity to their desired actions.

Brain computer interfaces have the potential to dramatically change how society functions. By utilizing brain computer interfaces to build neuroprosthetics, society becomes closer to complete integration with computers. This could mean the introduction of cyborg-like humans with capabilities that exceed normal biological capabilities (Clerc et al., 2016). More significantly**,** brain computer interface enabled prosthetics are making progress towards allowing those missing limbs to regain full functionality (H.A. Agashe et al., 2016). In my Sociotechnical Report, I will examine the impact of increasing integration of brain computer interfaces.

Creating more efficient and effective brain computer interfaces could lead to faster adoption of neuroprosthetics as a treatment for those missing functionality in their limbs. Machine learning algorithms make brain computer interfaces more efficient by improving their ability to identify brain signal characteristics and translate them into actions (Li et al., 2010). This could lead to a quicker and easier process of fitting neuroprosthetics to new users as the program will only need to adapt to the new user and will continuously improve as the user continues to use it. By incorporating machine learning into brain computer interfaces, a future in which people have the ability to regain complete function of lost or paralyzed limbs becomes much closer.

Machine Learning and Brain Computer Interfaces

The brain computer interface system is broken up into the following steps: signal acquisition, signal processing, device commands, and feedback (Shih et al., 2012). During signal acquisition, electrodes placed either on the scalp or surgically implanted near or on the brain record the electric signals produced by brain activity. Signals undergo some pre-processing, then go through feature extraction and a translation algorithm, which makes up signal processing. Commands are then transmitted to the desired device, which produces some sort of feedback to the user.

Signal processing, the step in which feature extraction and translation occurs, is where brain signals actually get converted into instructions for devices. This process begins with pre-processing, where irrelevant information that reduces signal quality is removed from the captured signal. Irrelevant information includes brain signals that are generated by eye or muscle activity (Li et al., 2010). Since there is no way to ensure users only think of one thing at a time, removing extra information is extremely important to isolate the signal of the desired action. Next, feature extraction, which is the isolation of useful signal features that reflect the user's intent, occurs through analyzing brain patterns in the time and frequency domain (Li et al., 2010). Finally, a translation algorithm identifies the useful signal and outputs the desired control signals to the external device.

The signal processing step, specifically feature extraction and translation is where machine learning can be extremely useful in creating effective and efficient brain computer interfaces. Without machine learning, users must undergo significant testing and training to build an accurate catalog of actions that maps their brain signals to their desired action. This process can be extremely tedious and repetitive as brain signals are not always the exact same. By introducing machine learning, this process could be significantly reduced by enabling the automatic generation and refinement of the translation dictionary. A machine learning algorithm will learn the brain signal characteristics for the user and continuously improve as the user continues to use the system.

Machine learning algorithms have the potential to greatly improve the quality of brain computer interfaces. Shifting some of the responsibility of extracting signal characteristics and translating them into control signals onto a machine learning algorithm reduces the amount of extensive testing by letting the computer extrapolate from existing data sets and adapt them to each individual user. Furthermore, computers can sift through data much faster than humans can so machine learning algorithms will be able to incorporate additional data sets into the process more efficiently.

Impact of BCI-Integrated Prosthetics

I am working on the topic of brain computer interfaces and prosthetics because I want to find out how brain computer interfaces can affect the lives of those requiring prosthetics. This is important because the loss of limb use leads to dramatic changes in quality of life and we should explore whether it is possible to reduce this impact. Furthermore, combining and/or replacing human biological functions with computers and machines will cause a ripple effect that will impact many aspects of common life.

Prosthetic devices are currently used by many patients to replace limbs lost due to trauma, disease, or other conditions. Early prosthetics were largely made from natural materials, such as wood, leather, and linen, and were extremely limited in their functionality (Prosthetics through the Ages, 2023). Since then, prosthetics have made large improvements in functionality, cosmetic appearance, and comfort. Prosthetics can now bend and rotate, though many need to be adjusted manually. Additionally, the materials used, such as plastic, aluminum, and silicon, are much lighter and more durable. However, not all prosthetics are suited for all aspects of life. For example, prosthetics made specifically for running differ in shape and material than those made primarily for daily use (Uustal, 2020). Furthermore, prosthetics are not a perfect recreation of lost limbs, which results in some permanently lost functionality.

Brain computer interfaces are an emerging technology that enables the decoding of brain signals into recognizable computer operations. Brain computer interfaces are divided into two major categories: invasive and non-invasive (Chaudhary et al., 2016). Invasive brain computer interfaces require the implantation of electrodes that are placed either directly on the brain or in the membrane surrounding the brain. Many invasive brain computer interfaces rely on electrocorticography (ECoG) readings from electrodes embedded in thin pads placed in the membrane that surrounds the brain (Shih et al., 2012). However, some rely on local field potentials, which are the electric potential recorded in the extracellular space in brain tissue (Chaudhary et al., 2016). The close proximity to the brain allows for more accurate readings of the electrical signals produced by the brain, but the surgery required to place those electrodes could lead to negative side effects. Furthermore, the body could reject the implanted electrodes causing a significant medical concern. Non-invasive brain computer interfaces, on the other hand, do not require surgery and mainly rely on electroencephalogram (EEG) readings from electrodes attached to the scalp, either individually or with an EEG cap (Chaudhary et al., 2016). These signals are much weaker due to damping by the skull, resulting in more difficult readings. Due to the weaker signals, non-invasive brain computer interfaces often need to amplify, filter, and decode the captured signals, and require training of the user to be most effective.

Brain computer interfaces have begun to enable the control of some prosthetic devices by merely thinking through the action. This breakthrough could eventually lead to the widespread use of neuroprosthetics, where most, if not all, prosthetics have close to full functionality of a biological human limb. However, the adoption of brain computer interfaces will cause ramifications that impact society. For example, the abilities of robotic limbs could exceed the natural capabilities of human limbs leading to robotically enhanced humans that could be used both for good and bad (Clerc et al., 2016). Furthermore, connecting humans to computers in such an integrated way could lead to security problems if the neuroprosthetics are able to be hacked (MacKellar, 2019). This paper will explore these issues by analyzing research on the use and risks of brain computer interface controlled prosthetics. These sources will be compared to determine what the average capabilities of brain computer interface controlled prosthetics are and what future capabilities will look like. Furthermore, sources analyzing the risks of brain computer interface controlled prosthetics will be collected to determine the severity of possible negative consequences.

Conclusion

Brain computer interface integrated prosthetics will have an impact on how society functions by enabling recuperation of full or exceeding functionality by those who have lost functionality in their limbs due to loss or paralysis. These humans will be more closely connected to a computer than any human has been in the past, leading to even more impacts such as the threat of hacking their interface. Additionally, humans with brain computer interfaces will become more like cyborgs as new developments allow more capabilities to be added. This research paper will address these impacts in depth in order to better define the potential future in which humans have increased their capabilities through robotic integration.

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