Utilizing Brain-computer Interfacing to Control Neuroprosthetic Devices

Cheyne Angy

A Thesis Proposal submitted in partial fulfillment
of the requirements for graduation
in the Honors Program
Liberty University
Spring 2016

Acceptance of Senior Honors Thesis

This Senior Honors Thesis is accepted in partial fulfillment of the requirements for graduation from the Honors Program of Liberty University.

____
Robert Melendy, Ph.D.
Thesis Chair

____
Charles Joseph, M.D.
Committee Member

____
James Long, M.E.M
Committee Member

____
Brenda Ayres, Ph.D.
Honors Director

4/14/16
Date

Abstract

Advances in neuroprosthetics in recent years have made an enormous impact on the quality of life for many people with disabilities, helping them regain the functionality of damaged or impaired abilities. One of the main hurdles to regaining full functionality regarding neuroprosthetics is the integration between the neural prosthetic device and the method in which the neural prosthetic device is controlled or manipulated to function correctly and efficiently. One of the most promising methods for integrating neural prosthetics to an efficient method of control is through Brian-computer Interfacing (BCI). With this method, the neuroprosthetic device is integrated into the human brain through the use of a specialized computer, which allows for users of neuroprosthetic devices to control the devices in the same way that they would control a normally working human function- with their mind. There are both invasive and non-invasive methods to implement Brain-computer Interfacing, both of which involve the process of acquiring a brain signal, processing the signal, and finally providing a usable device output. There are several examples of integration between Brain-computer Interfacing and neural prosthetics that are currently being researched. Many challenges must be overcome before a widespread clinical application of integration between Brain-computer Interfaces and neural prosthetics becomes a reality, but current research continues to provide promising advancement toward making this technology available as a means for people to regain lost functionality.

Utilizing Brain-computer Interfacing to Control Neuroprosthetic Devices

Neural prostheses, devices used to replace nonfunctioning motor, sensory, or cognitive abilities, date back all the way to 1957, when the first known cochlear implant was invented (Arafat, 2015). Since that time, significant advancements have been made in both the medical and engineering realms of neuroprosthetics. Neural prostheses now have the ability to allow individuals to overcome many disabilities in areas including visual, auditory, and motor functions, and have even expanded into the field of mental disabilities, showing promise in many applications including alleviating symptoms of brain trauma, speech deficiency, and Alzheimer's (Arafat, 2015). However, a more recent advancement in the field of neuroprosthetics is the Brain-computer Interface (BCI). Research began on BCIs in 1977, when the Pentagon's Defense Advanced Research Projects Agency (DARPA), along with the University of California, began to research and develop a method of communication based entirely on neural activity that has been generated by the brain, without the use of normal output pathways, which are peripheral nerves and muscles (He, 2005).

While BCI technology has the potential to be applied to a plethora of different external devices, several extremely beneficial applications for BCIs in neuroprosthetics are also in development. For example, by combining the abilities of a BCI and neural prostheses, both the ability to regain functionality, and the ability to control that function can be returned to someone with a disability. It is also possible for Brain-computer Interfaces to be used to efficiently and conveniently control neural prostheses, thereby effectively replacing nonfunctioning motor, sensory, or cognitive abilities in a disabled individual (Rupp et al., 2014).

In order to integrate neuroprosthetic and BCI technologies, both technologies must first be discussed separately. Neural prostheses all fall into two broad categories: external and implanted. These two categories have distinguishing features that will impact the integration between these neural prosthetics and a BCI. BCIs also fall into three similarly broad categories: Invasive, Non-invasive, and Partially Invasive. These categories indicate how the signal is obtained from the brain, which also has a significant impact on how BCIs can be integrated with neural prosthetics. The most prominent BCI platforms involve signal acquisition methods that fall into one of these three categories. The integration between BCIs and neural prostheses is currently in the development phase, but there have been numerous successes thus far. Nonetheless, the integration between these two technologies has many problems and limitations that must be overcome before clinical applications of the technology will be possible. Even so, the future biomedical applications of this technology have the potential to revolutionize the medical field.

Neural Prostheses

Neural prostheses are either implanted or external devices that are used to assist in the restoration of functions that have been lost as a result of neurological damage by electrically stimulating neurons (Shenoy et al., 2012). Numerous different neural prostheses have been used for a variety of different functions, but they can be divided into two broad categories: external and internal neuroprosthetic devices. External neuroprosthetic devices utilize surface electrodes, which are attached to skin in close proximity to peripheral nerves, and stimulate these nerves with electrical pulses (Rupp et al., 2014). The stimulation of these nerves has many medical applications, including physical therapy, where the stimulation of the nerves assists with retraining functionality in activities like walking, as well as pain relief (Rupp et al., 2014).

External Neural Prostheses

External neural prostheses can have the ability to restore functionality to paralyzed limbs by processing the electrical stimulation of nerves by the brain, as well as restore functionality to amputees by using the data obtained from the brain to produce movements and functionality in a prosthetic limb (Shenoy et al., 2012). This use is one of the most heavily linked applications of neural prostheses to Brain-computer Interfacing. External neural prostheses, although much more convenient than implanted neuroprosthetic devices face challenges of their own, mainly in data acquisition, which will be discussed in detail later in this paper (Patin, 2008).

Implanted Neural Prostheses

Implanted neuroprosthetic devices are generally much more difficult to use, since they are usually more complex, and must meet higher clinical standards, but they have equally impressive potential. Pacemakers, although not necessarily classified as neural prostheses by some definitions, are implanted electronic stimulators that have already made a huge impact in the medical community (Prochazka et al., 2001). Other examples of implanted neuroprosthetic devices include bladder-control implants which use radio-frequency controlled stimulators to control the detrusor muscle of the bladder, cochlear implants, and even visual implants of the retina (Prochazka et al., 2001). Implanted neural prostheses have many applications, and are currently widely used to improve the quality of life for people all over the world. However, implanted neural prostheses face several challenges that external neural prostheses do not.

First of all, implanted neuroprosthetic devices are required to be functional on a much smaller scale then external neuroprosthetic devices are, yet must also provide enough power to successfully transmit signals and function, making power consumption a huge factor concerning implanted neuroprosthetic devices, since they are not easily accessible for recharging or battery replacement (Sajda et al., 2008). Bio-compatibility is another factor that must be considered, since an implanted neuroprosthetic device must be made from certain, specific materials to ensure that it is not rejected by the immune system (Leuthardt, 2012). Lastly, data transmission from these devices must be both robust and secure. Although wireless transmission of data allows for a larger amount of data to be processed and stored, it also allows for the signal to be intercepted and used for malicious purposes (Mohan et al.). Despite these many issues that implanted neural prostheses face, the possible benefits far outweigh the challenges. Neural prostheses are already a huge asset to the medical community, and advancements in neuroprosthetic technology hold a promising future for the use of these devices.

Brain-computer Interfacing

While most methods of controlling neuroprosthetic devices require the use of the brain's normal pathway of peripheral nerves in order to obtain the information needed to make the device function, BCIs do not. Instead, BCIs utilize the brainwaves themselves to process and analyze the data that determines which functions the user is trying to implement (Arafat, 2015). The data itself must be analyzed and processed using a computer system due to its complexity, hence the name Brain-computer Interface. This is extremely helpful, especially in cases where the periphery nerves do not function properly, as in cases of paralysis, amputees, and people who are "locked-in," with full awareness, but no control over their bodies (Arafat, 2015). There are three different methods by which the brains signals can be obtained: Non-invasive, Invasive, and Partially Invasive (or Semi Invasive) BCI’s (Arafat, 2015).

Non-Invasive Brain Computer Interfaces

Non-invasive BCIs are the external implementations of the method. This method involves analyzing electroencephalogram signals, which are gained by reading brainwaves using electrodes that are attached to the scalp (Grabianowski, 2007). While this method is the most convenient of the three methods, it does not provide the amount of detailed information that could be recorded by implanted electrodes in the cortex via Partially Invasive or Invasive BCIs (Arafat, 2015). The disadvantage of having less detailed data is due to low selectivity in the surface electrodes, cable problems, and the need to change electrode positions regularly to ensure that the proper signals are being captured (Pfurtscheller et al., 2008).

Invasive Brain Computer Interfaces

Invasive BCIs, also known as Direct BCIs, describe the method by which electrodes are implanted directly into the brain (Kristenson, 2015). While this method allows for a much higher level of brain signal detail to be obtained, even allowing for reading information on the activity of small clusters of neurons, or even single neurons, it can only be implemented through procedures in which sensors are implanted directly into the gray matter of the brain (Arafat, 2015). Also, as with implanted neural prostheses, Invasive Brain-computer Interfacing faces a variety of other difficulties including difficulties in power consumption, biocompatibility, and long-term data reliability (Grabianowski, 2007). Since this method allows for signals from individual clusters of neurons in the brain to be measured by using micro-electrodes, it provides the clearest and therefore most desirable signal (Pedriera et al.).

Partially Invasive Brain Computer Interfaces

Partially Invasive BCIs involve electrodes being implanted within the skull but outside of the brain. This method can acquire much clearer brain signals than non-invasive methods, but does not provide signal information as detailed as Invasive BCI techniques (Kristenson, 2015). However, partially invasive methods do not have the dilemma of biocompatibility that invasive BCI methods have, so the user’s body is much less likely to reject the sensors implanted via this technique (Kristenson, 2015).

Integrating Brain-computer Interfacing with Neuroprosthetic Devices

The main challenge that neuroprosthetic devices face is proper functionality. In the case of many neural prostheses, certain parameters can be relatively easily preprogrammed into the device, such as pacemakers, which regulate a person’s heartbeat, or cochlear implants. However, some neural prostheses, such as prosthetic limbs, require integration with the brain in order to receive the information needed to direct the functions it carries out (Sajda et al., 2008). In order to effectively accomplish this, Brain-computer Interfacing is a method that shows an incredible amount of potential, which is already being carried out on some levels.

Although still in the early stages of research and development, many successes in the design and implementation of BCIs have already occurred, although most of the successes thus far have been confined to the laboratory. For instance, in 2002, researchers at Brown University were able to train monkeys to move the mouse on a computer screen using direct Brain-computer Interfacing, and in 2005, researchers were able to train monkeys to feed themselves with a robotic arm using the same method (Arafat, 2015). A more recent example occurred in 2010, when BCIs were successfully used to allow people with Amyotrophic Lateral Sclerosis to browse the internet with their mind, and in 2012, two long-term, tetraplegic stroke patients were able to control the reaching and grasping movements of a robotic hand using BCIs (Arafat, 2015). Although there is still a lot of room for improvement, Brain-computer Interfacing shows a lot of promise, especially when integrated with neuroprosthetic devices.

Utilizing BCIs to control neural prostheses has the potential to change the lives of many individuals who have limited functionality in their nervous system. Future advancement in the integration between BCIs and neural prostheses holds potential in not only the medical field, but in military, social, and even space exploration applications (Arafat, 2015). Even in its current stages, it can be seen that Brain-computer Interfaces can be used to replace nonfunctioning motor, sensory, or cognitive abilities in a disabled individual through integration with neural prostheses fairly effectively, which points towards a promising future for this technology. In time, efficiently and conveniently controlled neural prostheses could make the ability to completely regain functionality in motor, sensory, or cognitive abilities in a disabled individual become a reality.

The Utilization of BCIs

Integration between the human brain and a computer involves many hurdles that the user must overcome. Controlling a computer with one’s brain, at least up to this point, is not something that comes naturally to the user but rather involves a great deal of training to master (He, 2005). According to Dr. Wolpaw, Chief of the Laboratory of Nervous System Disorders at the New York State Department of Health, “most popular and many scientific speculations about BCIs start from the ‘mind-reading’ or ‘wire-tapping’ analogy, the assumption that the goal is simply to listen in on brain activity as reflected in electrophysiological signals and thereby determine a person’s wishes” (Wolpaw et al., 2002). However, Dr. Wolpaw et al. proceed to explain that this is not precisely how BCI’s function. Rather than simply reading signals that have been generated from the brain, a BCI must read the signal, and then alter the electrophysiological signal into electronic commands that can be used to dictate the reaction of the corresponding product that has been integrated into the BCI (Wolpaw et al., 2002). This is an incredibly sophisticated process, but in order for the human brain to operate the BCI correctly, it is imperative that feedback is provided to the brain. This feedback allows for alterations in brain activity to be made in order to improve and maintain functionality of the BCI.

Miranda provides a figure that shows the process of a BCI providing instructions to a neuroprosthetic, and subsequently receiving proprioceptive feedback from that neuroprosthetic (see Appendix A) (2015). In the figure electrode arrays implanted into the primary motor cortex (M1) record signals that indicate motor intent, which are then decoded and used to control the movement of a prosthetic arm (Miranda, 2015). Sensors on the robotic arm detect information on touch by physical contact with external objects and/or proprioception by analyzing the movement and position of the prosthetic limb (Miranda, 2015). Outputs from these sensors are then converted to patterns of stimulus pulses that are delivered by the implanted electrode arrays to the primary somatosensory cortex (S1), or other sensory regions of the brain, completing the feedback loop (Miranda, 2015).

Due to the nature of BCIs, this means that the user must learn to control specific electrophysiological signals, rather than proper muscle control (Wolpaw, 2002). The result of this is that the ability to properly and effectively utilize BCIs is a skill that must be learned, and is not simply an inherent trait of BCIs. However, the adaptive ability of the BCI itself is also a possibility to consider when determining how to optimize the control that a user has over a BCI. With both the brain and the BCI adapting to improve the performance and the ability to efficiently control neural prostheses, training time and effort can be decreased significantly, but are still relevant factors when using BCIs (Wolpaw, 2002).

In order for practical functionality of these BCIs, Dr. Wolpaw et al. set forth four essential elements that are imperative to the success of the integration of a BCI with neural prostheses (2002). The first is signal acquisition, which is the method by which the BCI system records an input signal directly from the brain, as an electrophysiological signal. The second element is signal processing, where the signal obtained by the first element is converted from the raw electrophysiological signal into an electronic command that can be sent to a neuroprosthetic device. This signal is then used by the third element, the device output, to dictate the control of the device according to the directions provided by the BCI. The final element for successful integration of a BCI with neural prostheses is the operation protocol, which determines any alterations that need to be applied to the BCI, as well as its operating parameters (Wolpaw et al., 2002).

Acquiring the Input Signal

According to Dr. Leuthardt, a neurosurgeon and assistant professor in the Department of Biomedical Engineering and Department of Neurological Surgery at the

Washington University School of Medicine, signal acquisition involves the “real-time measurement of the electrophysiological state of the brain” (2012). The electrophysiological signals that the brain produces are measured by electrodes that are applied with either the Invasive or the Non-invasive Brain-computer Interfacing methods that were mentioned previously. These electrodes measure voltage changes in the brain, and are able to translate these changes into a signal that can be relayed to the BCI for signal processing (Leuthardt, 2012).

Several prominent methods by which the electrophysiological signals that the brain produces can be read already exist, but there are also some newly emerging methods that could potentially prove to be equally effective methods. The first main method, electroencephalography (EEG), is the method used in non-invasive signal acquisition, reading voltage differences on the scalp to determine brain activity (Arafat, 2015). BCI’s are able to use the EEGs to “detect thought-modulated changes in electrophysiological brain activity and transform those changes into control signals” (Muller-Putz et al., 2008).

The other method is electrocorticography (ECoG), which is used to determine voltage changes in the brain during Invasive Brain-computer Interfacing (Arafat, 2015). ECoGs record voltage changes in the brain from inside the skull, and then transmit the data as a signal to the BCI. Similarly, field potentials use the Invasive Brain-computer Interfacing method to implant electrodes inside the parenchyma, which is the functional tissue that composes the brain, to measure brain activity (Patil et al., 2008). Lastly, microelectrodes, known as single units, can be used to measure the firing of individual neurons, and provide information on the brains electrical activity to the BCI in the form of a signal based on the firing of that individual neuron. Single units are also a form of Invasive Brain-computer Interfacing (Leuthardt, 2012). However, the vast majority of signal acquisition for BCIs is conducted using EEGs and ECoGs. All of these BCI platforms, although functional, are still in the process of being developed further, and will be discussed later in further detail.

Although signal acquisition currently depends almost exclusively on measuring voltage changes in the brain, several other methods exist that should theoretically also work as means to acquire a signal from the brain based on its activity. These methods include Magnetic Resonance Imagery (MRI), which can measure blood flow in the brain, Magnetoencephalography (MEG), which can measure alterations in magnetic fields within the brain, and Optical Signals (Arafat, 2015). Despite the fact that little research has been done regarding the use of these methods to provide signals for BCIs when compared to EEGs and ECoGs, these methods have the potential to be put into use as BCI development continues.

Signal Processing

Dr. Leuthardt states that there are two essential functions that the signal processing element must perform in order to be effective. These two functions are known as feature extraction and signal translation BCI (2012). Dr. Leuthardt describes feature extraction as the discernment between specific features in the signal that was acquired via the signal acquisition stage of the BCI, and will extract any significant information that it identifies as being imbedded in the signal (2012). He also notes that the signals provided by the electrodes have several properties that feature extraction must take into consideration in order to be able to perform its function, which is to ensure the successful capture of important data, as well preventing the capture of erroneous or irrelevant data (2012).

Somerset discusses these critical properties in his book *Intelligent and Biosensor*. The first critical property of brain signals is that they have a poor signal to noise ratio, which can make it difficult to distinguish the difference between the actual signals from erroneous ones (2010). Secondly, brain signals have high dimensionality, which, according to Somerset, means that features of the signals are extracted from several channels and from several time segments before being concatenated into a single feature vector. Also, it is extremely important that the feature extraction function contains time information, since the signals are generally related to time-based variation in their patterns (Somerset, 2010). Feature extraction must also take into account the non-stationary and non-linear nature of the brain signals. Finally, the limited amount of data that can be retrieved for training the system must be considered, since training is very demanding and time consuming for the user of the BCI. Keeping these factors in mind, the analysis of the information provided by electrodes can now be examined for feature extraction (Somerset, 2010).

The conversion of the raw data that is provided by electrodes during the signal acquisition element of the BCI requires some fairly complex analyses. The plethora of analyses that must be run also depends upon the method by which signal acquisition occurred in the previous element (Somerset, 2010). For example, an EEG or ECoG signal may need to be analyzed by assessing the frequency power spectra of the signal, event-related potentials, or cross-correlation coefficients, whereas when single units are utilized to acquire a signal from the brain, directional cosine tuning may be used as the method of analyzing the signal (Somerset, 2010). Many different forms of analyses can be used for feature extraction, but the results of these analyses allow for the compacted information that is obtained during these analyses to be used in the next function inside this element: signal translation. Dr. Cichocki explains the signal processing method for a BCI developed by the Riken Brain Science Institute, specifically for controlling hand movements (2006). The figure provided by Cichocki shows the preprocessing of the brain signals, which translates the brain signals into a spectral matrix (see Appendix B). A feature matrix is then used in the feature extraction section of signal processing, and will process the extracted features in a classification system. The classification system will then decide on the action to be taken based on the extracted features (Cichocki, 2006).

During the signal translation function of the signal processing element, a complex translational algorithm is responsible for relating the important features that have been extracted from the brain signal to output signals, which will control an output device (Schalk, 2010). Traditionally, signal translation has been accomplished through procedures that primarily use conventional classification/regression algorithms. Examples of these translation procedures include neural networks, linear discriminant analysis, support vector machines, and linear regression (Schalk, 2010). However, these methods cannot always allow for the non-stationary nature of brain signals.

In order to compensate for the abrupt and unpredictable changes in brain signals, the signal translation algorithm may also include a whitening procedure, which “produces signals with zero mean and a defined variance such that the output device does not have to account for changes in brain signal characteristics that are not related to the task”

(Schalk, 2010, p. 28). Essentially the signal processing element of the BCI is responsible for extracting the features of the brain signal that accurately reflect the users intentions, through feature extraction, and translating those signal features into output signals that can be used to control an output device.

Device Output

After the brain signal has been processed and converted into a form that is readable, it is sent to an output device. Numerous output devices currently have the potential to be used by the BCI network, ranging from computer screen cursors to robotic arms, or even controlling intrinsically physiological functions, such as moving a limb or bladder control (Leuthardt, 2012). The most common and well researched BCI output device is a computer cursor, which the BCI dictates the movement of on a computer screen. According to Thompson et al., who are developing a Multi-Purpose BCI Output Device (MBOD), which has the potential to interface between a BCI and multiple different output devices, four main design goals must be considered when creating a BCI output device (2012).

Device-controller compatibility. The first design goal for all BCIs is device-controller compatibility. It is essential for the BCI to be able to integrate with the output device in order to ensure that the directions given by the BCI are able to quickly and seamlessly be related to the output device (Thompson et al., 2012). The four major categories that Thompson lays out in order to determine the root purpose of the device are augmentative and alternative communication (AAC), environmental control systems (ECS), computer access (CA) and movement (M), all of which require a unique integration with BCIs in order to ensure proper device-controller compatibility.

Throughout these different categories, the three most common types of input that an output device will accept are a switch, a mouse, or a keyboard, and each type of input requires a specific input from a BCI to function correctly (Thompson et al., 2012). However, as research on methods such as the MBOD continue, it may be possible for device-controller compatibility to encompass several types of devices, regardless of the type of input that the device requires.

Input device compatibility. The second design goal considers the opposite side of the spectrum from the previous design goal. Since a number of different BCIs are currently being developed idiosyncratically, there will certainly be differences in the types of output that these BCIs produce (Thompson et al., 2012). The most efficient way to do this would be to include a companion program that translates custom or alternative BCI inputs into a common framework that the device can utilize to implement the instructions given by the BCI.

Convenience. The device should be user friendly, allowing for simple integration between the output device and the BCI. Thompson et al. liken this to the modern “USB plug-and-play” devices, which facilitate in the discovery and installation of the device immediately upon its integration with a computer system (2012). Thompson et al. accomplish this by incorporating three features into his MBOD: drivers, power, and flexible output capabilities (2012). In essence, the ideal output device should be able to be easily integrated with the BCI to ensure an efficient and user-friendly product. However, while this is especially prevalent for the MBOD, most neuroprosthetic devices will be connected for long periods of time, making the necessity of reintegration with the BCI less relevant.

Intuitive command structure. The final design goal, according to Thompson et al., involves incorporating an intuitive connection between the input device and the output device (2012). The switch, the continuous-output BCI modalities (e.g. a computer mouse), and a full keyboard modality are the three output modalities that Thompson incorporates into his MBOD, which allows for easier integration between multiple different output devices (Thompson et al., 2012). The importance that these differing modalities all be included in the command structure of the BCI can be easily seen in cases where the BCI will be utilizing different output devices, as with the MBOD. However, many neuroprosthetic devices involve a long-term connection, which does not need to incorporate multiple command structures.

The development of effective output devices is not a trivial matter, and requires a great deal of research and testing. The design used to ensure effective communication between the BCI and the output device is essential to the success of any BCI output device. Nevertheless, although the design of the output device is integral to the successful operation of the BCI, the burden does not fall solely on the output device to interpret the commands given by the BCI.

BCI Operation Protocol

In order for the BCI to operate successfully, and to successfully transmit readable data to the output device, the BCI must abide by specific operation protocols. This means that the BCI must have a consistent methodology in the way that users interact with the BCI, and how the BCI processes that interaction (Leuthardt, 2012). This includes how users turn the BCI on or off, how they control the speed at which commands are implemented, the control of the kind of or speed at which feedback is provided, as well as the various other governing factors of the BCI that the user controls. These interactions between users and BCIs are critical for real-world applications of the BCI (Leuthardt, 2012). The protocols set in place are what allow the BCI to provide consistent results during the interaction between a BCI and its user.

Brain Computer Interfacing Platforms

Currently there exist three general categories of BCI Platforms that have the potential to be used in clinical applications: Electroencephalography-based Systems, Electrocorticography-based Systems, and Intermediate Modality Systems (Leuthardt, 2012). The categories are determined based on the source of the brain signal that controls the BCI. Since the specifics of EEGs and ECoGs have been discussed previously, this section will primarily focus on the progress in the development of these systems as a whole.

Electroencephalography-Based Systems

As previously discussed, the non-invasive nature of the EEG makes it the most practical and convenient method by which to obtain a brain signal, which is the reason that it is one of the most commonly used systems to study BCI potential. A considerable amount of success with EEG-based systems has already been made, allowing for human control of a computer cursor in both two and three dimensional scenarios (McFarland et al., 2008). However, the limitations of the detail of the brain signals acquired by EEGs provide a serious limitation on the system as a whole. These limitations prevent the systems from acquiring specific details provided by the brain signals, such as position or velocity of a movement, which seriously inhibits the potential for EEG systems to be used in applications involving neuroprosthetic devices (Leuthardt, 2012). This system has also proven to require a relatively long training period before users are able to effectively communicate with the BCI (Leuthardt, 2012). These combined limitations pose a serious problem to the future of EEG-based BCIs.

Electrocorticography-Based Systems

ECoG-based systems have been gaining momentum in the scientific community as the most practical and robust option for clinical applications with a BCI (Leuthardt, 2012). ECoGs have been previously discussed, being noted for the quality of brain signal that can be obtained using this method, although the invasive procedures in the form of subdural electrode implants required to implement ECoG technology detract from the appeal of this technology. The robustness of the signal provided by ECoG makes up for this detrimental quality however, overcoming challenges faced by EEG-based systems like prolonged user training, allowing users to achieve a high level of control in the span of only a few minutes (Leuthardt, 2012).

A comparison of the signals acquired from EEG and ECoG methods, as well as those from implanted electrodes is provided by Buzsáki, Anastassiou, and Koch (see Appendix C) (2012). By comparing the signals, it is clear that ECoG signals provide the most distinct signal changes. Also, ECoG-based systems are able to obtain higher quality signals from the brain, even reading the high frequency gamma signals that EEG-based systems cannot read due to poor signal-to-noise ratio limitations (Leuthardt, 2012). Despite the invasive nature of ECoG-based BCI systems, the robustness of the signals provided by this system, coupled with the benefits that are provided to the BCI by the high quality brain signals that ECoG-based systems read, ensures that ECoG technology will be continued to be researched, and could be the leading technology for BCI integration with neuroprosthetics in the future.

Single Neuron-Based Systems

The third most prominent system being researched for its applications with BCI technology is the single neuron-based system, which implements the microelectrodes that measure voltage outputs from single neurons that were referenced earlier (Leuthardt, 2012). This system would allow for the optimal amount of electrical information to be gained from the brain, since each neuron is individually monitored. The system would function via a network of these extremely small (approximately 20 microns in diameter) neuron monitors, which monitor the activity levels in neurons throughout the Parenchyma layer of the brain, and providing very detailed signals for the BCI to utilize (Leuthardt, 2012).

Due to the high level of detail, the single neuron-based system gives users very high-fidelity control of the BCI, providing the users with what is arguably the highest level of control for BCI applications (Leuthardt, 2012). However, this method of system faces several challenges that make it less effective than the ECoG-based system. The first major problem that the single neuron-based system faces is the potential dangers of implanting microelectrodes into the Parenchymal layer of the brain. According to Dr. Leuthardt, implantation of the microelectrodes into the Parenchymal layer could potentially cause neural or vascular damage in the area surrounding the implanted microelectrode (2012). Also, these microelectrode could very easily be rejected by the body’s immune system, resulting in neural cell death, or encapsulation of the microelectrodes in tissue, which could isolate it from the electrical signals of the intended neuron, rendering the microelectrode useless (Leuthardt, 2012). Another drawback of single neuron-based systems is the difficulty of widespread implementation of the system. Construction of the system requires an intensive neural surgery to implant the microelectrodes, making the widespread clinical application of this technology implausible.

Current BCI Integration with Neural Prosthetics

A great deal of progress has been made in the area of clinical applications of BCI integration with neuroprosthetic devices, but a lot of research and testing still needs to be done before many of these applications can become widely available to the public. BCI integration with neuroprosthetics must meet several goals to provide a functional and practical application of the technology in real life situations. First, the system must operate in a closed loop, functioning without need for information or power from an external system. Second, the system must have channels to relay information from the neuroprosthetic device back to the BCI, so that the feedback provides the BCI with relevant information. Next, the system must be robust, being able to function for long periods of time without major errors. Also, the BCI must be able to adapt to physical changes within the brain itself. Lastly, the system must be able to withstand environmental factors that the device could endure, such as water resistance (Rothschild, 2010). With such rigorous requirements, it is easy to see why many of these applications are not in widespread clinical applications. However, the progress that has been made in many of most influential areas of neural prosthetics will now be discussed.

Although the most important successes in the integration of BCIs with neuroprosthetics have been confined to the laboratory, where the research was done on able-bodied subjects rather than the target population of disabled subjects, these successes have immense potential. One such success is the InendiX BCI, which allows users to type messages, produce synthesized speech, or control some external devices (Shih et al., 2012). The impact that a commercialized version of this BCI could have on the disabled populace is huge, allowing for many people with communication disabilities to gain or regain that functionality.

Visual Prosthetics

Visual Prosthetics are one of the highest priorities in the biomedical community, and there has been a great deal of research regarding a biomedical solution to blindness caused by retinal degeneration (Rothschild, 2010). The degeneration of photoreceptor cells in the retina is one of the main areas of research for visual prosthetics. These prosthetics have been applied in one of three possible solutions to photoreceptor dystrophy: prosthetic retinal implants, prosthetic optic nerve implants, and prosthetic visual cortex implants (Rothschild, 2010). Each method has potential drawbacks, either having non-ideal functionality replacement, difficult surgical implications or both.

One current project that involves BCI integration with the visual neuroprosthetics, led by Daniel Palanker, a professor in the Department of Ophthalmology and Hansen Experimental Physics Laboratory at Stanford University, involves using a “pocket” computer that is wirelessly connected to photovoltaic subretinal prosthesis (Saunders et al., 2014). This computer processes images from a miniature camera that has been mounted onto goggles, and transmits them to the subretinally implanted photodiode array. These then convert the light into electrical pulses that stimulate nearby inner retinal neurons, and transmit a visual image to the brain (Saunders et al., 2014). Although a great deal of progress still needs to be made before clinical applications of visual prostheses become widespread, projects such as these provide concrete evidence that a cure to blindness within the grasp of the biomedical community.

Auditory Prosthetics

The most commonly used auditory prosthetic is the cochlear implant, which functions by stimulating the Sensory Epithelium of the Basilar Membrane to produce auditory stimuli (Rothschild, 2010). Most auditory prosthesis function independently from BCIs, since prosthesis such as the cochlear implant are capable of functioning without the need of a computer to process information and relay it to the brain. However, several projects are in development in which a BCI implements auditory prosthetics to provide feedback to the brain when other neuroprosthetic devices are being used (Rothschild, 2010). Although auditory neuroprosthetics are not very prevalent in the field of BCI integration with neuroprosthetics, they still have potential to provide a substantial impact on BCI technology and methodology.

Replacement Limb Prosthetics

The most popular target audience of BCI integration with neuroprosthetics is undoubtedly replacement limb prosthetics. The majority of current research is done with the end goal of helping either those who have lost limbs, or those who have non-functioning limbs. Due to this, replacement limb prosthetics and their integration with BCIs is some of the most advanced technology in the field. In fact, BCI integration with replacement limb prosthetics has progressed to the point that a non-invasive hybrid FES orthosis for restoration of hand and elbow function was developed, providing a satisfactory amount of functionality with brain signals provided by EEGs, which is a far more desirable method than invasive BCIs (Rohm et al., 2013). In 2005, the first Tetraplegic BrainGate BCI was implemented, allowing a man to control a prosthetic arm directly with his mind (Arafat, 2015). Since then, much advancement has been made in the field, such as wireless interaction between a BCI and the prosthetic limb (Arafat, 2015). Some of the most current research on BCI integration with neuroprosthetics involves improving the accuracy of BCI signal processing and decreasing the time and effort needed to learn to use BCIs through the use of both visual and proprioceptive feedback (Ramos-Murguialday et al., 2012). Since neuroprosthetic devices that function as limb replacements and are controlled by BCIs are already in clinical trials, the primary goal of research in this area is now focused on increasing the efficiency and effectivity of these devices.

Problems and Limitations of BCI Integration with Neural prosthetics

Several problems may be encountered when attempting to integrate BCIs with neural prosthetics, and many limitations that current BCI technology faces when integrating with neural prosthetics. The main issues that need to be addressed before BCI integration with neural prosthetics can be widely disseminated among the target population, the disabled, includes problems with signal acquisition and accuracy, difficulties in the user interaction with the BCI, biocompatibility issues, and system robustness.

The first problem that will be addressed is the difficulty in acquiring accurate and detailed brain signals, and converting those signals into the proper command for the BCI to transmit to the neuroprosthetic device. As discussed previously, the different method of signal acquisition all have their benefits and drawbacks. However, none of the signal acquisition methods have the level of detail that is ideal for translating the brain signals into commands by the BCI (Grabianowski, 2007). Although the current technology allows for enough detail for the BCI interaction with neuroprosthetic devices to function, most clinical applications only result in about 60% to 75% accuracy in signal translation (Mak et al., 2009). In order to have effectively functioning BCI integration with neuroprosthetics, so that it can be applied on a large scale, a more accurate translation from brain signal to device command needs to be developed.

The next difficulty of BCI integration with neural prosthetics is the aspect of user interaction. Currently, the process of learning to use BCIs, especially non-invasive BCIs, is both difficult and extended. Use of BCIs is reported to cause fatigue to the users, who must concentrate for prolonged periods of time when using BCIs that have been integrated with neuroprosthetics (Mak et al., 2009). Before BCIs become widely implemented, the method in which BCIs are controlled needs to become more natural, and require less concentration from users.

Another problem, which is exclusive to invasive BCIs, is the issue of biocompatibility. Since a continued presence of electrodes in the brain promotes the formation of a sheath around the electrode that is composed partly of reactive astrocytes and microglia, which could lead to neural cell death and tissue resistance, which would electrically isolates the device from the surrounding neural tissue, the electrodes for invasive BCIs need to be created from biocompatible material (Leuthardt, 2012). Although some functional biomaterials already exist, there is still ongoing research to find biomaterials that are better suited for BCI applications (Leuthardt, 2012).

The last issue that will be discussed that BCIs must overcome before widespread application of BCI integration with neural prosthetics becomes possible is system robustness. Current technology requires that a BCI be robust. For invasive BCIs, it is essential that any implanted electrode or neuroprosthetic be functional for long periods of time for it to be an effective solution. Also, due to the complexity of the computing, current technology requires that a fully functioning mobile BCI contain a minimum of ten pounds of equipment, but as computers continue the trend of becoming both smaller and more powerful, this problem should be remedied in the relatively near future (Mak et al., 2009).

The Future of BCIs

As scientists, engineers, and researchers continue the development of BCIs, the enormous potential of these systems will become increasingly evident. Researchers like Dr. Ibriham Arafat predict that by the year 2030, bionic ears, bionic eyes, and prosthetic limbs will be completely functional on a large scale, and will be controlled through some variation of BCI, giving many disabled people the ability to function completely normally (2015). More conservative predictions, however, have noted that BCIs technology is still in its infancy, and since it target audience is a relatively small segment of the population, it is unlikely to attract the commercial interest that would be needed to quickly advance BCI technology in the medical field (Mak et al, 2009). Nonetheless, outside of the medical field, BCIs have vast potential in the commercial field, and predictions of BCI integration in both entertainment and communication technologies do create a potential for massive advancement in BCI technology (Arafat, 2015). In this case, the advancement in BCI technology could then be integrated with medical applications, essentially allowing commercial uses of BCI technology to fund the research needed to advance BCIs in the medical field.

Conclusion

Brain-computer Interfacing is some of the most exciting technology that is currently being developed, and the integration of these BCIs into neuroprosthetic devices has potential to revolutionize the medical field. Although BCI technology, especially in regards to its application with neuroprosthetic devices, is still entrenched in the research phase of its development, this technology has the potential to have an enormous impact in the future medical field. Neuroprosthetic technology is also rapidly progressing through research, as the cortical physiology that underpins the way a human brain encodes intentions is beginning to be understood (Leuthardt, 2012). The amalgamation of these two technologies results in an exciting prospect in which future prosthetic devices, whether they are visual prosthetics, auditory prosthetics, or prosthetic limbs, will function exactly like their natural human counterparts. Although this technology has many challenges that must be overcome before a widespread clinical application of BCI integration with neural prosthetics becomes a reality, current research is steadily progressing towards a future in which disabled people have the ability to completely regain lost functionality.

References

Arafat, I. (2015). Brain–computer interface: past, present & future. *Academia,* Retrieved from http://www.academia.edu/1365518/Brain_Computer_Interface_Past_Present_and_Future

Bensmaia, S.J. & Miller, L.E. (2014) Restoring sensorimotor function through intracortical interfaces: progress and looming challenges. *Nature Reviews Neuroscience, 15*, 315. doi:10.1038/nrn3724

Buzsáki, G., Anastassiou, C. A., & Koch, C. (2012). The origin of extracellular fields and currents—EEG, ECoG, LFP and spikes. *Nature Reviews Neuroscience*. *13*, 407–420. doi:10.1038/nrn3241

Cichocki, A. (2006) Towards a real time human brain-computer interface with neurofeedback: improving differentiability by blind source separation. *Riken BSI News, 34*. Retrieved from http://www.brain.riken.jp/bsi-news/bsinews34/no34/research1e.html

Grabianowski, E. (2007). How brain-computer interfaces work. *HowStuffWorks*, Retrieved from http://computer.howstuff works.com/ Brain-computer-interface.htm

Rupp, R., Kleih, S. C., Leep, R., Millan, J. R., Kübler, A., & Müller-Putz, G. R.(2014) Brain–Computer Interfaces and Assistive Technology. In G. Grübler & E. Hildt, (Eds.), *Brain-computer-interfaces in their ethical, social and cultural contexts* (pp. 7-38). Netherlands: Springer.

He, B. (2005). Brain-computer interface. In *Neural engineering* (pp. 85-121). New York: Kluwer Academic/Plenum.

Kristenson, A. (2015). Brain-computer interfaces and neuroprosthetics: an introduction. *Brighter Brains*, Retrieved from http://brighterbrains.org/articles/ entry/Brain-computer-interfaces-and-neuroprosthetics-an-introduction

Leuthardt, E. (2012). The evolution of brain-computer interfaces. *National Academy of Engineering, 42*(1), Retrieved from https://www.nae.edu/Publications/Bridge/ 57865/ 58598.aspx

Mak, J. N., & Wolpaw, J. R. (2009). Clinical applications of brain-computer interfaces: current state and future prospects. *IEEE Reviews in Biomedical Engineering*, *2*, 187–199. http://doi.org/10.1109/RBME.2009.2035356

McFarland, D. J., Sarnacki, W. A., & Wolpaw, J. R. (2010). Electroencephalographic (EEG) control of three-dimensional movement. *Journal of Neural Engineering*, *7*(3). http://doi.org/10.1088/1741-2560/7/3/036007

Millán, J. R., Rupp, R., Müller-Putz, G. R., Murray-Smith, R., Giugliemma, C., Tangermann, M., … Mattia, D. (2010). Combining brain–computer interfaces and assistive technologies: state-of-the-art and challenges. *Frontiers in Neuroscience*, *4*, 161. http://doi.org/10.3389/fnins.2010.00161

Miranda, R. A., Casebee, W. R., Hein, A.M, Judy, J.W., Krotkov, E.P., Laabs, T.L., Manzo, J.E, … & Ling, G. S. (2015). DARPA-funded efforts in the development of novel brain–computer interface technologies. *Journal of Neuroscience Methods, 244*, 52-67. doi:10.1016/j.jneumeth.2014.07.019

Mohan, G., Ganesan, N., & Gulvady, K. (n.d.). Healthcare using technology. *Mumbai University*. Retrieved from http://www-scf.usc.edu/~nganesan/Papers/ HealthCareUsingTechnology.pdf

Muller-Putz, G., Rupp, R., & Pfurtscheller, G. (2008). Graz brain-computer interface: control of neural prosthetics for the upper extremity. *Applied Sciences on Biomedical and Communication Technologies*. Retrieved from http://ieeexplore.ieee.org/xpls/icp.jsp?arnumber=4712627. doi:10.1109/ISABEL.2008.4712627

Patil, P., & Turner, D. (2008). The development of brain-machine interface neuroprosthetic devices. *Neurotherapeutics: The Journal of the American Society for Experimental NeuroTherapeutics, 5*(1), 137-146.

Pedriera, C., Martinez, J., & Quiroga, R. (n.d.). Neural prostheses: linking brain signals to prosthetic devices. Retrieved from https://www2.le.ac.uk/ departments/engineering/research/bioengineering/neuroengineering-lab/Publications/PID924857.pdf

Pfurtscheller, G., Muller-Putz, G., Scherer, R., & Neuper, C. (2008). Rehabilitation with brain-computer interface systems. *Computer, 41*(10). Retrieved from http://ieeexplore.ieee.org/xpls/icp.jsp?arnumber=464066

Prochazka, A., Mushahwar, V. K., & McCreery, D. B. (2001). Neural prostheses. *The Journal of Physiology*, *533*(1), 99–109. http://doi.org/10.1111/j.1469-7793.2001.0099b.x

Ramos-Murguialday, A., Schurholz, M., Caggiano, V., Wildgruber, M., Caria, A., & Hammer, E. (2012). Proprioceptive feedback and brain computer interface (BCI) based neural prosthetics. *PLoS ONE,* 7(10). Retrieved from http://journals.plos.org/plosone/article?id=10.1371/journal.pone.0047048 doi:10.1371/journal.pone.0047048

Rohm, M., Schneiders, M., Muller, C., Kreilinger, A., Keiser, V., Muller-Putz, G., & Rupp, R. (2013). Hybrid brain-computer interfaces and hybrid neural prosthetics for restoration of upper limb functions in individuals with high-level spinal cord injury. *Artificial Intelligence in Medicine*, *59*(2). Retrieved from http://dl.acm.org/citation.cfm?id=2543061

Rothschild, R. (2010). Neuroengineering tools/applications for bidirectional interfaces, brain–computer interfaces, and neuroprosthetic implants: a review of recent progress. *Frontiers in Neuroengineering*, *3*(112). Retrieved from http://dx.doi.org/10.3389/fneng.2010.00112

Sajda, P., Muller, K., & Shenoy, K. (2008). Brain-computer interfaces. *IEEE Signal Processing Magazine*, *25*(1), 16-28. Retrieved from http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=4408438

Saunders, A. L., Williams, C. E., Heriot, W., Briggs, R., Yeoh, J., Nayagam, D. A., … Allen, P. J. (2014). Development of a surgical procedure for implantation of a prototype suprachoroidal retinal prosthesis. *Clinical & Experimental Ophthalmology*, *42*(7), 665–674. http://doi.org/10.1111/ceo.12287

Schalk, G. (2010). Brain sensors and signals. In *A Practical Guide to Brain-computer Interfacing with BCI2000.* London: Springer-Verlag London.

Shenoy, K., & Chestek, C. (2012). Neural prosthetics. *Scholarpedia, 7*(3). Retrieved from http://www.scholarpedia.org/article/Neural_Prosthetics

Shih, J. J., Krusienski, D. J., & Wolpaw, J. R. (2012). Brain-computer interfaces in medicine. *Mayo Clinic Proceedings*, *87*(3), 268–279. http://doi.org/10.1016/j.mayocp.2011.12.008

Somerset, V. (2010). Signal processing and classification approaches for brain-computer interface. In *Intelligent and Biosensor*. Rijek: InTech

Thompson, D. E., & Huggins, J. E. (2011). A multi-purpose brain-computer interface output device. *Clinical EEG and Neuroscience*, *42*(4), 230–235. Retrieved from http://www.ncbi.nlm.nih.gov/pmc/articles/PMC3269095/

Wolpaw, J., Birbaumer, N., Heetderks, W., McFarland, D., Peckham, P., Schalk, G., ... Vaughan, T. (2000). Brain-computer interface technology: a review of the first international meeting. *IEEE Transactions on Rehabilitation Engineering*, *8*(2), 164-173. Retrieved from http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=847807

Wolpaw, J., Birbaumer, N., Mcfarland, D., Pfurtscheller, G., & Vaughan, T. (2002). Brain–computer interfaces for communication and control. *Clinical Neurophysiology 113,* 767-791. Retrieved from http://www.cs.cmu.edu/~tanja/BCI/BCIreview.pdf

Appendix A

Idealized bidirectional Brain–computer Interface for closed-loop prosthetic control from Bensmaia et al. (2014).

http://www.nature.com/nrn/journal/v15/n5/full/nrn3724.html

Appendix B

Diagram an EEG-BCI classification method for imaginary hands movements developed by the Riken Brain Science Institute from Cichocki (2006).

http://www.brain.riken.jp/bsi-news/bsinews34/no34/research1e.html

Appendix C

A comparison of a macroscopic recording via electroencephalography, a mesoscopic recording through electrocorticography, and implantable electrode signals from Buzsáki et al. (2012).

http://www.nature.com/nrn/journal/v13/n6/full/nrn3241.html