Designing Brain Machine Interfaces for Rehabilitation: A Study

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Abstract

Brain Machines Interfaces provide a digital channel for communication in the absence of the biological channels. Brain machine interfaces are considered as potential devices to rehabilitate patients with motor nerve disorders namely those who have lost their motor functions as well as communication functions. In this paper a study is conducted to understand the functions of the motor cortex region of the brain and its role in the designing of brain machine interfaces for rehabilitation. A survey on the current brain interfaces is also presented.

Keywords

Brain Machine Interfaces, Rehabilitation Robotics, EEG

1. Introduction

Locked-in syndrome is now becoming a popular term. Patients with this disease loose total control over their motor functions and communication channels. The patients are however aware of their surroundings due to a still active brain. Modern life support and medication help these patients to live longer lives prolonging their personal and social dependencies on the society. Current research on brain signals has shown the feasibility of using brain signals to directly control devices like computers. An extended approach is to use this signal to control devices like prosthetic arms and wheel chairs. This paper aims at highlighting some of the disease which disrupt the biological communication channels and the possibilities of brain signals to control external devices through a digital link.

Many disorders can disrupt the neuromuscular channels used by the brain to communicate with and control its external environment. Amyotrophic lateral sclerosis (ALS), brainstem stroke, brain or spinal cord injury, cerebral palsy, muscular dystrophies, multiple sclerosis, and numerous other diseases impair the neural pathways that control muscles or impair the muscles themselves. They affect nearly two million people in the United States alone, and far more around the world .Those most severely affected may lose all voluntary muscle control, including eye movements and respiration, and may be completely locked in to their bodies, unable to communicate in any way. In the absence of methods for repairing the damage done by these disorders, there are 3 options for restoring function. The first is to increase the capabilities of remaining pathways. Muscles that remain under voluntary control can substitute for paralyzed muscles. People largely paralyzed by massive brainstem lesions can often use eye movements to answer questions, give simple commands, or even operate a word-processing program; and severely dysarthric patients can use hand movements to produce synthetic speech[1]. The second option is to restore function by detouring around breaks in the neural pathways that control muscles. In patients with spinal cord injury, Electromyography (EMG) activity from muscles above the level of the lesion can control direct electrical stimulation of paralyzed muscles, and thereby restore useful movement .The final option for restoring function to those with motor impairments is to provide the brain with a new, non-muscular communication and control channel, a direct brain–computer interface (BCI) for conveying messages and commands to the external world. At present, only EEG and related methods, which have relatively short time constants, can function in most environments, and require relatively simple and inexpensive equipment, offer the possibility of a new non-muscular communication and control channel, a practical BCI. EEG based communication attracted little serious scientific attention until recently, for at least 3 reasons. First, while the EEG reflects brain activity, so that a person's intent could in theory be detected in it, the resolution and reliability of the information detectable in the spontaneous EEG is limited by the vast number of electrically active neuronal elements, the complex electrical and spatial geometry of the brain and head, and the disconcerting trial to-trial variability of brain function. The possibility of recognizing a single message or command amidst this complexity, distortion, and variability appeared to be extremely remote. Second, EEG-based communication requires the capacity to analyze the EEG in real-time, and until recently the requisite technology either did not exist or was extremely expensive. Third, there was in the past little interest in the limited communication capacity that a first generation EEG-based BCI was likely to offer. Recent scientific, technological, and societal events have changed this situation.

2. Motor Functions and the Brain

The anatomical region of the brain known as primary motor cortex is the focal region for muscle contractions. Stimulations in this region elicited highly localized muscle contractions at various locations in the body. This mapping is represented somatotopically on the motor cortex, where the surface area devoted to controlling the movements of each body part varies in direct proportion to the precision of the movements that can be made by that part

The motor cortex is divided into the premotor area (or premotor cortex) and the supplementary motor area. The premotor cortex is believed to help regulate posture by dictating an optimal position to the motor cortex for any given movement. The supplementary motor area, for its part, seems to influence the planning and initiation of movements on the basis of past experience. The mere anticipation of a movement triggers neural transmissions in the supplementary motor area. Besides the frontal cortex, the posterior parietal cortex clearly plays a role in voluntary movements, by assessing the context in which they are being made. The parietal cortex receives somatosensory, proprioreceptive, and visual inputs and then uses them to determine such things as the positions of the body and the target in space. It thereby produces internal models of the movement to be made, prior to the involvement of the premotor and motor cortices. The parietal lobes are themselves closely interconnected with the prefrontal areas, and together these two regions represent the highest level of integration in the motor control hierarchy. It is here that the decisions are made about what action to take. In brain imaging, when subjects are asked to move their thumbs, activity is observed in the posterior parietal and somatosensory areas [2].

3. Electroencephalography

EEG is a technique that reads scalp electrical activity generated by brain structures. The EEG is measured directly from the cortical surface. When brain cells or neurons are activated, the local current flows are produced. EEG measures mostly the currents that flow during synaptic excitations of the dendrites of many pyramidal neurons in the cerebral cortex. Only large populations of active neurons can generate electrical activity recordable on the head surface; weak electrical signals detected by the scalp electrodes are to be massively amplified. The cortex is a dominant part of the central nervous system. The highest influence of EEG comes from electric activity of cerebral cortex due to its surface position [3].

3.1 EEG Research History

The existence of electrical currents in the brain was discovered in 1875 by an English Physician Richard Caton. In 1924 Hans Berger a German neurologist amplified these electrical signals using ordinary radio equipment and coined the term *electroencephalogram* to describe brain electric potentials in humans. In 1934 Adrain and Mathews published a paper verifying the concept of ‘human brain waves’ [or EEG] and identified regular oscillations around 10 to 12 Hz which they termed as alpha rhythm. Brain waves have been categorized into four basic groups: beta (>13 Hz); alpha (8-13 Hz); theta (4-8Hz); delta (0.5 -4 Hz) [3]. Until early 1990s, most of the researches on EEG were focused on analyzing brain related disease and sleep patterns. The early 1990s witnessed a rapidly growing body of research involving detection of human brain responses and putting these techniques to appropriate uses to help disabled people. Most of the research during this period involved surgically implanting electrodes to acquire the signals. With the introduction of external electrodes during the turn of the century [2000] EEG has initiated the development of BCI to control the cursor of computers. Currently this research has been directed towards producing BMI which can control a prosthetic arm or a wheelchair [1].

3.2 International 10-20 System

To perform consistent testing of EEG recordings a system called the International 10-20 electrode placement system was developed [4]. This system created a method of labeling electrode locations to be used worldwide. The EEG electrodes are placed on the scalp at 10 and 20 percent of a measured distance. Figure 1 shows the international 10-20 Electrode placement positions [4].

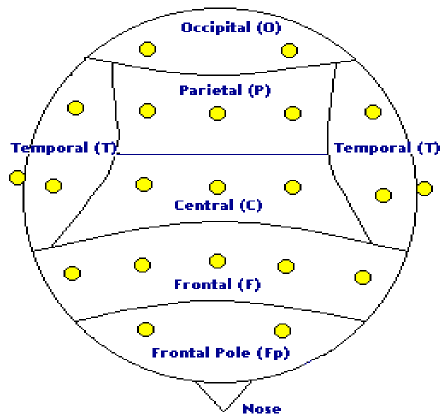

Figure 1 International 10-20 Electrode Placement System

4. Brain Machine Interface: Techniques

BMI can be broadly classified into two types, Sensory and Motor. Sensory BMI are designed to replace a damaged organ such as retinal prosthesis to help the blind and cochlear implants for the deaf. The Motor BMI, on the other hand, seeks to translate electrical brain activity that represents intent to move into useful commands to external devices. Sensory BMI requires very accurate placement of a few tiny electrodes that stimulate the appropriate site in the brain, and the device’s job is to simulate the role of the appropriate sensory organ as accurately as possible. In motor BMI, the electrodes are placed “anywhere” in the appropriate cortex area and their number is much higher. The decoding problem for motor BMI is much harder, since there is little knowledge of how the motor cortex encodes information, and also due to only a small fraction of the cells is being probed [1]. There are two basic types of motor BMI: non-invasive and invasive. Research on non-invasive BMI started in the 1980s by measuring brain electrical activity over the scalp.

Brain computer interfaces [BCI] have been developed to move computer cursors. Through training, subjects can learn to control their brain activity in a predetermined fashion that is classified by a pattern recognition algorithm, and converted into one of several discrete commands usually cursor actions (up/down, left/right) on a computer display. The computer presents a set of possibilities to the users, and they choose one of them through these cursor actions, until a task is completed. This approach, requiring only signal amplification and classification is known as a brain computer interface. BCI classification algorithms combine machine learning techniques with biomedical domain knowledge [1].

Five main techniques are adopted in designing brain computer interface [5].

a. P300 Detection

The P300 component is a positive going evoked response potential (ERP) in the EEG with a latency of about 300ms following the onset of a rarely occurring stimulus the subject has been instructed to detect. Detecting the P300 response reliably requires averaging the EEG response over many presentations of the stimuli.

b. EEG mu-rhythm Conditioning

Subjects' mu-rhythm [Appears at 9-11 Hz this activity appears to be associated with motor cortex [6]. Amplitudes are detected while training them to move a computer cursor up and down on the screen. Results also implied that frequency bands other than mu and beta ranges may contain useful information.

c. Visual Evoked Potential Detection

Electrodes are placed over the visual cortex to detect changes in evoke potentials when the subject concentrates on a particular block out of the 64 blocks on a computer screen.

d. EEG Pattern Mapping

In this technique the EEG patterns are detected and classified for a particular action. Readiness potentials or EEG patterns are studied during experiments such as moving joystick in four directions.

e. Detecting lateral hemisphere differences

Induced lateral differences in relative brain hemisphere activation are studied during experiments where subjects hear arguments through left, right or both headphones.

4.1 Need for Brain Machine Interfaces

EEG signals are being studied to rehabilitate people with motor disorders. About 10 million people all over the world suffer from neurodegenerative diseases such as cerebral palsy or amyotrophic lateral sclerosis [locked-in people], stroke and paralysis [7]. These diseases impair their ability to control their muscles and are unable to grasp objects, work with appliances or communicate in any way except through their brains. In Malaysia the increase of stroke and paralytic patients is of major concern, modern life support technology allows these individuals even those who are locked–in, to live long lives, so that the personal, social and economic burdens of their disabilities are prolonged and severe.

There is a growing concern in the community today to help these disabled people and improve their living conditions. The Malaysian government has implemented many social welfare schemes such as rehabilitation and independent living policies to improve the conditions of these patients through rehabilitation service and by provision of assistive and rehabilitative devices.

4.2 Motor Disabilities and Restoring Options

Many disorders can disrupt the neuromuscular channels through which the brain communicates with and controls its external environment. Amyotrophic lateral sclerosis, brain stem stroke, brain or spinal cord injury, cerebral palsy, muscular dystrophies, multiple sclerosis and numerous other diseases impair the neural pathway that controls the muscles themselves. Peripheral nerve disorders like Guillain-Barré Strohl Syndrome, Chronic Inflammatory Demyelinating Polyneuropathy, Polyneuropathies, Diabetic Neuropathies, Mononeuropathies - including carpal tunnel syndrome and ulnar neuropathies Peripheral Nerve Injuries,Amyotrophic Lateral Sclerosis (ALS) , Radiculopathies , Small Fiber Neuropathies, and Occupational Neuropathies also effect the communication channels and these patients can be provided rehabilitation through BMI .

Restoring these motor functions can be done depending on the severity of the impairment. In case of partial impairments, restoration can be done by increasing capabilities of remaining pathways, such as substituting muscles under control for paralyzed muscles, namely eye movements in the case of brainstem impairment and hand movements in the case of severely dysarthric patients. One other option is by rerouting around the neural breakaways that control muscles, for example using EMG signals from areas above the level of nervous break to restore useful movements. When the above two options are not possible the only solution to restore motor function is to provide a non muscular control channel directly from the brain to devices such as wheelchairs. Patients with diseases like locked-in syndrome and partial paralysis are not able to produce any type of movement. Independent to this the sensory and cognitive functions of the brain are not or partially affected. These patients are very much aware of their environment but are not able to communicate through speech or eye movements. Though many physiological signals such as EMG, fMRI, MEG and PET are available, research has proved that only EEG signals and related methods which have short time constants, can function in most environments and require relatively simple and inexpensive equipment that offer the possibility of a new non-muscular channel for a practical BMI [9].

The development of BMI to control wheel chairs is still under proof of concept stage. The next section analyses some of the research efforts and studies towards developing a BMI for motor movement and subsequent control of a powered wheel chair.

4.3 Brain Machine Interfaces and Rehabilitation

EEG based BCI/BMI has been under study since the early nineties. BCI only provide interface between brain and computer, so far BCI have been developed to control computer cursors on the other hand BMI are more focused towards developing interfaces between brain and devices like prosthetic arms , wheelchairs etc.. BMI are used to replace impaired motor nerves and to provide an alternative communication channel to control devices like a wheelchair. Research studies have been conducted to study the EEG signals evoked by motor movements and recognition of these signals towards developing interfaces. Most research studies on EEG are currently focused on developing algorithms for classification of EEG signals related to movement. A review of the literature shows that three methods have been adopted in extracting the EEG feature data, namely Autoregression, Independent Component Analysis and Neural Networks. This section reviews some of these research studies.

A DSLVQ classifier for feature selection of EEG signals was proposed by Pregenzer et al [10]. Two different types of experiments are used to show that DSLVQ is an appropriate feature selector for a BCI. The first experiment employs DSLVQ to select the most distinct electrode positions from a large number of possible positions. The second experiment uses DSLVQ to analyze the importance of 1-Hz bands of EEG power spectra for the prediction of three different types of movement. The conclusions of this study show that the most important electrode position and frequency bands are not identical for all subjects.

Guger and et al [10] use Common Spatial Pattern (CSP) filters to analyze real-time EEG signals. Experiments involved three subjects. Twenty seven EEG electrodes overlaying the whole primary and sensory motor cortex are used. The method proposed uses covariance to design common spatial patterns and is based on simultaneous diagonalization of two covariance matrices. The decomposition of the EEG leads to new time series which is optimal for discrimination of two populations. The patterns are designed such that signals resulting from filtering with CSP have maximum variance for left trials and minimum variance for right trials and vice versa. The research demonstrates that CSP can be used to anise EEG signals in real time in order to give feedback to subjects as classification accuracy improved with few days of trials.

Pfurtscheller and et al [11,12] have studied the separability of left and right motor imagery using autoregressive parameters. Four subjects were used in the experimental process and EEG, EMG and EOG signals are recorded from electrodes overlapping sensory motor area. Subject specific frequency components are selected using the DSLVQ classifier. Due to the laterality of the EEG patterns, the side [left or right] of the imagined movement can be determined with an online error between 10 to 31.8 %. The online classification of subject specific frequency bands were analyzed by a neural network. An overall improvement of classification was achieved using the off-line adaptive autoregressive model [ARR]. However the ARR method is found to be sensitive to artifacts, therefore artifacts must be controlled.

Haselsteiner and Pfurtscheller [13] have compared two different neural network topologies to classify a single trial EEG data from a BCI. The classifiers are the MLP and the FIR MLP. The static weight of the standard MLP is replaced with finite impulse response filters in the FIR MLP. The study shows that FIR MLPs performed better can standard MLP with lesser error rates.

Mahalanobis distance-based classifiers are analyzed by Babiloni et al [14], to classify the diagonal and full covariance matrix features of the EEG signals. EEG data are recorded from four electrodes placed in the C3, P3, C4 and Imagined hand movement recognition using Low Resolution Surface Laplacian and Linear P4 position of International 10-20 system. These classifiers were able to detect imagination of hand movements with a classification accuracy of 98%.

Another imagined hand movement recognition using Low Resolution Surface Laplacian and Linear Classifier is proposed by Concotti et al [15] which use nine electrodes; the classifiers have an accuracy of 90%.

Neural network based classifiers of EEG features have been investigated by some researchers [16, 17,18]. Back propagation neural classifiers have also been used to analyze the EEG signals related to mental tasks.

Research on BMI is being extended to the next stage of translating them to control signals to operate devices.

Conclusions

BMI is still at the proof-of-concept stage, currently this work is undertaken by bio and neuroscience researchers. The contributions from computer engineers, psychologists and mathematician are essential to take this to the next stage. The developments of more accurate data models that carry more spatio-temporal information from the spikes in the motor cortex are required. The signals are non-gaussian and no stationary, so they are very difficult to model well with present algorithms [1].

So far, control BMI has focused on cursor movements, applying this concept to a mechanical hand or a device such as a wheelchair will prove to be more challenging. Although the theoretical and technical problems are difficult, BMI research is at a very exciting phase, thanks to the tight integration of research in computer science, engineering, and neuroscience. There is optimism about impacting the daily lives of paraplegics in the same way that sensory BMIs benefited hearing impaired patients [1].

The non-invasive BMI has potential applicability beyond the restoration of lost movement and rehabilitation in paraplegics and would enable normal individuals to have direct brain control of external devices in their daily lives. Therefore, the impact of BMI on our society promises to surpass that of any earlier digital technology.

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