REPORT DOCUMENTATION PAGE	Form Approved OMB NO. 0704-0188

1. REPORT DATE (DD-MM-YYYY)	2. REPORT TYPE	3. DATES COVERED (From - To)
27-08-2015	MS Thesis	-

4. TITLE AND SUBTITLE	5a. CONTRACT NUMBER
The Neuroscience of Brain Computer Interface: Cognitive Intuition and Analysis	W911NF-13-1-0118
	5b. GRANT NUMBER
	5c. PROGRAM ELEMENT NUMBER 206022
6. AUTHORS Lavoris Langley	5d. PROJECT NUMBER
	5e. TASK NUMBER
	5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAMES AND ADDRESSES	8. PERFORMING ORGANIZATION REPORT NUMBER
North Carolina A&T State University 1601 East Market Street Greensboro, NC 27411 -0001	
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS (ES)	10. SPONSOR/MONITOR'S ACRONYM(S) ARO
U.S. Army Research Office P.O. Box 12211 Research Triangle Park, NC 27709-2211	11. SPONSOR/MONITOR'S REPORT NUMBER(S) 62815-NS-REP.2

12. DISTRIBUTION AVAILIBILITY STATEMENT

Approved for public release; distribution is unlimited.

13. SUPPLEMENTARY NOTES

The views, opinions and/or findings contained in this report are those of the author(s) and should not contrued as an official Department of the Army position, policy or decision, unless so designated by other documentation.

14. ABSTRACT

A BCI is a direct communication pathway between the brain and an external device. The utilization of BCIs consists of assisting, augmenting or repairing human cognitive or sensory-motor functions. The operation of BCIs consists of recording the electrical activity along the scalp via various synchronous activity including electroencephalography (EEG), electrocardiography (ECG), electromyography (EMG), magnetoencephalography (MEG) and electronystagmography (ENG). BCIs create a new

15. SUBJECT TERMS

neuroscience, brain computer interface, cognition, intuition, information visualization

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	15. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT	b. ABSTRACT	c. THIS PAGE			Younho Seong
UU	UU	UU	UU		19b. TELEPHONE NUMBER 336-285-3734

Standard Form 298 (Rev 8/98)
Prescribed by ANSI Std. Z39.18

Report Title

The Neuroscience of Brain Computer Interface: Cognitive Intuition and Analysis

ABSTRACT

A BCI is a direct communication pathway between the brain and an external device. The utilization of BCIs consists of assisting, augmenting or repairing human cognitive or sensory-motor functions. The operation of BCIs consists of recording the electrical activity along the scalp via various synchronous activity including electroencephalography (EEG), electrocardiography (ECG), electromyography (EMG), magnetoencephalography (MEG) and electronystagmography (ENG). BCIs create a new non-muscular channel that is used to relay the intentions of an individual to external devices such as a computer, speech synthesizer, assistive appliance or neural prostheses. The use of BCIs is appealing for individuals with severe motor disabilities by partially or fully restoring functionality of a bodily member.

The Neuroscience of a Brain Computer Interface: Cognitive Intuition & Analysis

Lavoris L. Langley

North Carolina A&T State University

A thesis submitted to the graduate faculty

in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE in INDUSTIRAL & SYSTEMS ENGINERING

Department: Industrial & Systems Engineering

Major Professor: Dr. Younho Seong

Greensboro, North Carolina

2014

Abstract

A Brain-Controlled Interface (BCI) is a device that monitors and captures cerebrum transmissions of a subject who has the intent to initiate the movement of a bodily member. BCIs serve the purpose of restoring communication between the cerebrum and bodily member(s) that are immobilized. BCIs function by recording the electrical activity in the cerebrum via the scalp (electroencephalography), surface of the cerebrum or within the cerebral cortex (grey matter). These brain signals are transmitted to command signals that drive prosthetic limbs and or computer displays. This literature review is a meta analysis that serves the purpose of researching the neuroscience and psychology of cognitive decision-making, specifically intuition and analysis, and which parts of the cerebrum that controls these functions.

Introduction

A BCI is a direct communication pathway between the brain and an external device. The utilization of BCIs consists of assisting, augmenting or repairing human cognitive or sensory-motor functions. The operation of BCIs consists of recording the electrical activity along the scalp via various synchronous activity including electroencephalography (EEG), electrocardiography (ECG), electromyography (EMG), magnetoencephalography (MEG) and electronystagmography (ENG). BCIs create a new non-muscular channel that is used to relay the intentions of an individual to external devices such as a computer, speech synthesizer, assistive appliance or neural prostheses. The use of BCIs is appealing for individuals with severe motor disabilities by partially or fully restoring functionality of a bodily member.

BCI research is a relatively young multidisciplinary field that integrates research from neuroscience, physiology, psychology, engineering, computer- science and other technical and health-care disciplines. This review discusses cognition, and the process of decision-making. Furthermore, this review will analyze what occurs during the decision-making process including: hemodynamics, brain signals recorded and the measurement used to enumerate the rhythms during the cognitive task.

Literature Review

Cognition

Cognition is a term and concept that has many different interpretations and definitions, and is studied by various disciplines including psychology, philosophy, science and linguistics. Consequently, how cognition is defined varies across the various disciplines that study this mental activity. *Merriam-Webster* defines cognition as "conscious mental activities, the activity of thinking, understanding learning and remembering". *Psychology Today* defines cognition as "simply thinking". Within the scientific community, cognition is defined as mental processing including attention, working memory, reasoning, problem solving and decision-making. Within the confines of this paper, cognition will be discussed from the perspective of cognitive neuroscience, and how cognitive processes arise from activity within the brain.

During the cognitive process, sensory inputs are transformed, reduced, elaborated, stored, recovered and used by the brain. The prevalent stance in modern cognitive science is that cognitive processes arise from functionally organized brain process. Cognitive neuroscience is a discipline that seeks to understand how these processes are initiated, where they originate, and which areas of the brain show increased activity when a particular cognitive task is being performed. A realization of cognitive processes is the fact that they are not static, but dynamic and even the simplest percept, memory or decision is a process that requires time to unfold. The relationship between brain dynamics and cognitive dynamics can be described as a sequence of brain areas that "light up" during the various stages in the performance of a cognitive task. Contemporary research seeks to understand, describe and give an emerging view of brain processes as reverberations or reentrant activity in a complex neural network.

Intuition

Intuition is often thought to be a 'gut feeling', 'hunch' or a 'six sense'. Intuition is essentially knowing without knowing how one knows. The debate over what intuition is and its use is due to the difficulty of determining how intuition informs clinical decision-making. It is often thought wise to make a decision when an individual is cool, calm and collected and above all, rational. However, recent research and advances in cognitive neuroscience suggests that it is impossible for human beings to function effectively without using 'gut feelings' when making decisions. Cognitive research suggests that there is nothing mystical or magical about intuitive processes, and that they are neither paranormal nor irrational. Intuitive processes evolve from extended experience and learning, consisting of the mass of facts, patterns, concepts, techniques and generally formal knowledge or beliefs which are impressed on the mind of an individual. Intuition is a 'synthetic' psychological function in that it captures the totality of a given situation; it allows individuals to synthesize isolated bits of data and experiences into an integrated picture. Intuition is a holistic perception of reality that transcends rational ways of knowing [11].

Intuition is subconscious

Intuition lies along a continuum of consciousness and subconsciousness. However, only a fraction of the lessons individual experiences becomes fully crystallized as facts and are thus accessible to the conscious mind. Intuition is mostly subconscious; individuals draw from this reservoir of innumerable experiences that are stored within the brain without conscious thought. Yet some of these stored experiences or knowledge in the subconscious are more readily available than others via intuition. Parikh (1994) observed that intuition could well be a form of intelligence at a level individuals simply cannot access with rational thought. According to Parikh, intuition consists of "accessing the internal reservoir of cumulative experience and expertise developed over a period of years, and distilling out of that a response, or an urge to do or not to do something, or choose from some alternatives- again without being able to understand consciously how we get the answers" [11].

Intuition is complex

Parikh stated that intuition can "deal with systems more complex than those which can be figured out in our conscious minds". Due to this complexity, it is challenging to measure intuition with models. Intuition embraces subtle quantitative and qualitative with balance, as a result intuition is probably superior to a purely rigorous quantitative model. Most of the rational-analytical models are confined because of the assumption of linearity. Intuition permits an overcoming of the limits of rationality in an unstable environment [11].

Intuition is quick

Intuition is a process that occurs very quickly. It is a smooth automatic performance of learned behavior sequences which often short-circuit a step-wise decision making, therefore allowing an individual to know almost instantly what the best course of action is. The process consists of compressing years of experience and learning into split seconds [11].

Intuition is not emotion

Intuition is often mistrusted on the premise that is springs from emotion as opposed to reason, but intuition does not come from emotion. Vaughan (1990) observed that fear and desire both interfere with intuitive perception. If an individual happens to be anxious, angry or emotionally upset, they are not likely to be receptive to the subtle messages, which can come into consciousness via intuition. Similarly, Ray and Myers noted in 1990 that fear, anxiety and wishful thinking can get in the way of the clear operation of intuition [11].

Intuition is not biased

A consensus in cognitive psychology research suggests that intuitive decision-making; rather it be subjective or the use of the mind, is full with cognitive biases. Based upon this proposition in the above line of research, it leaves the question of how individuals are able to make decision at all, much less effective decisions. However, there is another growing body of research that suggests that intuition is not necessarily a biased process, and it can be uncannily accurate. Ilgen and Feldman noted that research has focused on bias and invalidity almost exclusively, thus creating the impression that valid judgment based upon intuition are rare. Ilgen and Feldman also argued that the cognitive process by which valid judgments are made is exactly the same as the one that generates biased ones. An illustration of this premise can be explained by the forces determining an arrow's flight, which are the same whether or not the arrow is on target. Seebo and Harung hypothesized that if intuitive synthesis suffers from biases or errors, so does rational analysis [11].

Intuition is part of all decisions

Intuition, even those based on the most concrete and hard facts are central to all decisions. In 1990, Goldberg stated: "seldom be used exclusively; by its very nature, prediction deals with the unknown, and we can calculate or measure only what is known… At the very least, a forecaster has to use intuition in gathering and interpreting data and in deciding which unusual future events might influence the outcome. Hence in virtually every decision there is always some intuitive component". In sum, intuition is not an irrational process, it is based on a deep understanding of a situation. It is a complex phenomenon that draws from a vast storage of knowledge in our subconscious, and is rooted in past experience. Intuition is quick, but not necessarily biased as presumed in research conducted previously on rational decision-making.

Analysis

Analysis is a complex process to define. Analysis consists of detailed examination of the elements or structure of a particular entity, usually as a basis for discussion or interpretation. The purpose of a Cognitive Task Analysis (CTA) is to systematically define the decision requirements and psychological processes used by individuals in accomplishing results. A task analysis explains the process and inputs that are being currently used to accomplish results. As a consequence, a task analysis defines what individuals and teams are either doing or should be doing in order to contribute to current results. In completing a needs assessment the task analysis is a vital tool for mutually informing the diagnosis of needs as well as the detection of potential remedies for improving performance. Cognitive analysis methods focus on the psychological process underlying the competition of a task. Use cognitive analysis whenever complex decisions are required, such as when multiple contributing variables and options must be weighed by the performer, and few observable behaviors identified. Subtle cues from the performance context and the experience of expert performers are often discovered through this analysis technique.

Advantages of CTA

- A cognitive task analysis generates detailed, precise information on the nature of expert performance in a specific task of interest.
- When implemented correctly, cognitive task analysis techniques are highly valid sources of information on expert cognitive processes.

- A cognitive task analysis provides systematic procedures (rather than hit-or-miss steps) for ascertaining expert cognitive process.

Disadvantages

- Analysis of the data gathered during a cognitive task analysis can be time-intensive
- Cognitive task analysis does not always capture other non-cognitive attributes necessary for accomplishing results (such as, physical capabilities, access to resources, and interpersonal relationships).
- The results of a cognitive task analysis can be misleading when expert performers have performance capacities beyond that of others (i.e. a cognitive task analysis can be done with high performing professional athletes but implementation of cognitive process along will not duplicate performance).

Brain-computer interface

A Brain-Computer interface (BCI) is an artificial intelligence system that is a direct pathway communication between the brain and an external device. A BCI functions by allowing a subject to interact with their surroundings via the measurement of neural activity that occurs during the mental process without the use of peripheral nerves and muscles. A BCI specifically operates by using control signals generated from EEG activity. The artificial intelligence of a BCI system can recognize a certain set of patterns in brain signals consisting of five consecutive stages: signal acquisition, preprocessing or signal enhancement, feature extraction, classification and the control interface. The signal acquisition stage captures the brain signals, and may also perform noise reduction and artifact processing. The preprocessing stage prepares the signal in a suitable form for further process. The extraction stage identifies discriminative information in the brain signals that has been recorded. After a signal is measured, it is mapped onto a vector containing effective and discriminate features from the observed signals. The classification stage classifies the signals taking the feature vectors into account. It is essential that good discriminative features be chosen to achieve effective pattern recognition, in order to decipher the intentions of the user. Finally, the control interface stage translates the classified signals into meaningful commands for any connected device, such a computer or a wheelchair [2].

Neuroimaging in BCIs

BCIs use brain signals to collect information for user intentions by rely on the recording stage, where brain activity is measured and translated into tractable electrical signals. Electrophysiological and hemodynamic are two types of brain activity that may be monitored. Electrophysiological activity is generated by electro-chemical transmitters that exchange information between the neurons, the neurons generate ionic currents that flow within and across neuronal assemblies. This large variety of current pathways can be simplified as a dipole conducting current from a source to a sink through the dendritic truck, these intracellular currents are known as primary currents. Conservation of electric charges means that primary currents are enclosed by extracellular current flows that are known as secondary currents; electrophysiological activity is measured by electroencephalography (recording of electrical activity along the scalp), electrocorticography (recording of electrical activity from the cerebral cortex using electrodes), magnetoencephalography (mapping brain activity by recording magnetic fields) and electrical signal acquisition in single neurons [2].

Electroencephalogram (EEG) and magnetoencephalogram (MEG) attempts to revel and describe the oscillatory activity of the brain, and how this relates to the dynamics of cognitive performance. There are limitations of EEG and MEG brain computer interfaces (BCI) including the relatively poor spatial resolution of EEG and MEG, although MEG spatial resolution can approach that of fMRI. Another limitation of these imagining techniques is EEG and MEG constitutes only part of the brain's relevant dynamics, consequently, models may not be complete and they may only illustrate what can be accomplished within the dynamical approach [1].

Current non-invasive BCIs

Most current BCIs obtain the relevant information from cerebrum activity through EEG. EEG is by far the most widely and commonly used neuroimaging modality due to its high temporal resolution, relative low cost, high portability and few potential risks to the users. BCIs that are based on EEG consist of a set of sensors that acquire EEG signals from different brain areas. However, the quality of EEG signals is affected by the scalp, skull and many other layers as well as background noise. Yet, noise is key to EEG and to other neuroimaging methods, as it reduces signal to nose ratio (SNR), and therefore the ability to extract meaningful information from the recorded signals [2]. Non-invasive BCI approaches have been successfully used to reacquire basic forms of communication, and to control neuroprostheses and wheelchairs by severely and partially paralyzed patients.

Motor recovery has been limited due to the need for brain signals with a higher resolution, despite the outstanding utility of non-invasive BCI applications. As a result of the limitations of non-invasive BCIs, intracranial methods-which requires electrodes being placed directly on the exposed surface of the brain-such as electrocorticography (ECoG) or intracortical neuron recording were introduced in efforts to improve the quality of brain signals monitored by BCIs. Most researchers agree that movement restoration through prostheses with multiple degrees of freedom can only be achieved through invasive approaches, and that it is unlikely that the power of non-invasive modalities will be enhanced in the near future [2]. While it appears that invasive modalities are indispensible for accurate neuroprostheses control, this issue is not yet entirely clear and some opinions disagree with this conjecture. Contrary to this established opinion, Wolpaw suggested that performance in multidimensional control may be independent of the recording method, and that further refinements of recording and analysis techniques will probably increase the performance of both invasive and non-invasive modalities. Nevertheless, the latest studies in neuroprostheses control appear to indicate that invasive modalities have inherent advantages in neuroprostheses control applications [2].

Invasive modalities

Invasive modalities require the implant of microelectrode arrays inside the skull, which poses significant health risks, therefore restricting their use in experimental settings. Electrocorticography and intracortical neuron recording are two invasive modalities that can be found in BCI research. EEG places electrodes on the surface of the cortex, either outside the dura mater (epidural electrocorticography), or under the dura mater (subdural electrocorticography). Intracortical neuron recording consists of electrodes implanted inside the cortex. There are several issues with invasive BCIs that has to be addressed before they become suitable for long-term applications. Tissue acceptance has to be addressed initially, for which reason proposals exist for electrodes with neurotropic mediums that promote neuronal growth to improve biocompatibility [2]. The solution for long-term invasive applications of BCIs may lie in the development of nanotechnologies, which may lead to the development of nano-detectors to be implanted inertly in the brain. Secondly, a link between the microelectrode and external hardware that uses wireless technology is needed to reduce the risk of infection; wireless transmission of neuronal signals has previously been tested in animals [2]. Lastly, continuous stress caused by plugging and unplugging the recording system may lead to tissue damage, or system failure.

Neuroimaging Method	**Activity measured**	**Direct/Indirect Measurement**	**Temporal resolution**	**Spatial resolution**	**Risk**	**Portability**
EEG	Electrical	Direct	~0.05 s	~10 mm	Non-invasive	Portable
MEG	Magnetic	Direct	~0.05 s	~5 mm	Non-invasive	Non-portable
ECoG	Electrical	Direct	~0.003 s	~1 mm	Invasive	Portable
Intracortical neuron recording	Electrical	Direct	~0.003 s	~0.5 mm (LFP) ~0.1 mm (MUA) ~0.5 mm (SUA)	Invasive	Portable

fMRI	Metabolic	Indirect	~1 s	~1 mm	Non-invasive	Non-portable
NIRS	Metabolic	Indirect	~1 s	~5 mm	Non-invasive	Portable

Table 1: Summary of neuroimaging methods [2]

Explanation of each neuroimaging modality

Electroencephalography (EEG)

EEG measures the electric activity in the brain caused by the flow of electric currents during synaptic excitations of the dendrites in the neurons, and is extremely sensitive to the effects of secondary currents [2]. EEG is the most widespread recording modality due to how easily signals are recorded in a non-invasive manner via electrodes placed on the scalp. However, there are disadvantages to EEG modality. These challenges include the quality of the signals, due to the fact that the signals have to cross the scalp, skull and many other layers. As a result, EEG signals in the electrodes are weak, hard to acquire and of modest quality. This technique is also affected by background noise generated either inside the brain, or externally over the scalp.

Magnetoencephalography (MEG)

MEG is a non-invasive imaging technique that registers the magnetic activity of the brain via magnetic induction. MEG measures the intracellular currents flowing through dendrites, which produce magnetic fields that are measurable outside of the head [2]. The neurophysiological processes that produce MEG signals are identical to those that produce EEG signals. However, while EEG is extremely sensitive to secondary current sources, MEG is even more sensitive to those of primary currents [2]. The advantage of MEG is that magnetic fields are less distorted by the skull and scalp than electric fields [2].

Superconducting quantum interferences devices detect magnetic fields, which are extremely sensitive to magnetic disturbances produced by neural activity [2]. The electronic equipment that measures magnetic brain activity is cooled to almost -273 degrees Celsius to facilitate sensor superconductivity. Effective shielding from electromagnetic interferences is required for MEG. The electronic equipment is installed inside a magnetically shielded room, which attenuates the effects of magnetic fields from external sources.

When compared to EEG, MEG provides signals with higher spatiotemporal resolution than EEG. Consequently the training time needed to control a MEG BCI is reduced, and reliable communication is sped up. MEG has also been successfully used to localize active regions inside the brain. Contrary to the advantageous features of MEG, MEG is not often used in BCI design because MEG technology is too bulky and expensive to become an acquisition modality suitable for everyday use. When compared to EEG, MEG based BCIs are still at an early stage [2].

Electrocorticography (ECoG)

ECoG is a technique that records electrical activity from the cerebral cortex by means of electrodes placed directly on the surface of the brain. ECoG provides higher temporal and spatial resolution when compared to EEG, as well as higher amplitudes and a lower vulnerability to artifacts such as blinks and eye movement. In spite of these advantageous features, ECoG is an invasive recording modality, which requires a craniotomy to implant an electrode gird, posing significant health hazards. As a consequence of this realization, the first studies on ECoG were with animals. These early studies conduced on animals were conducted with the goal of evaluating the long-term stability of signals from the brain that ECoG could acquire [2]. The results showed that subdural electrodes could provide stable signals over several months. Nevertheless, the long-term stability of the signals acquired by ECoG is currently unclear. Contemporary experiments conduced with the use of monkeys have shown that ECoG can perform at a high level for months without any drift in accuracy or recalibration [2]. The results from these experiments include hand positions and arm joint angels could be successfully decoded during asynchronous movement, and the development of minimally invasive protocols to implant the probes required for ECoG [2].

ECoG research that has been conducted with the use of humans has been used for the analysis of alpha and beta waves or gamma waves produced during voluntary motor action [2]. Regarding the use of ECoG in BCIs systems, Levine *et al.* [2] designed a BCI which classified motor actions on the basis of the identification of the event-related potential (ERP) using ECoG. Levine *et al.* [2] showed for the first time that an ECoG-based BCI could provide information to control a one-dimensional cursor, as this information is more precise and more quickly acquired than by EEG-based BCIs. Years later, Schalk *et al.* [2] presented a more advanced ECoG-based BCI which allowed the user to control a two-dimensional cursor. The results of these studies might make it more feasible for people with severe motor disabilities to use ECoG-based BCIs for their communication and control needs [2].

Intracortical Neuron Recording

Intracortical neuron recording is a neuroimaging technique that measures electrical activity inside the gray matter of the brain [2]. It is an invasive recording modality, which requires the implant of microelectrode arrays inside the cortex to capture spike signals and local field potentials from neurons.

Three signals can be obtained via intracortical neuron recording: single-unit activity (SUA), multi-unit activity (MUA), and local field potentials (LFPs) [2]. SUA is obtained by high-pass filtering (>300 Hz) of the signal of a single neuron. MUA is obtained in the same way, but the signals may come from multiple neurons. LEPs are extracted by low-pass filtering (<300 Hz) of the neuron activity in the vicinity of an electrode tip. LFPs are analog signals whereas SUA and MUA measure the spiking activity of single neurons, and can be reduced to discrete events in time [2].

Intracortical neuron recording provides spatial and temporal resolution that is much higher than EEG recording. As a result, intracortical signals may be easier to use than EEG signals. However, signal quality may be affected by the reaction of cerebral tissue to the implanted recording microelectrode [2] and by changes in the sensitivity of the microelectrode, which may be progressively damaged over the course of days and years [2]. The user can naturally adapt to these slow changes in the relative sensitivity of the microelectrode, without the need for specific retraining. Nevertheless, periodic recalibrations of electrode sensitivity may be necessary [2].

The first attempts in the intracortical neuron-recording field were made in animals. Multielectrode arrays have been used to record neural activity from the motor cortex in monkeys or rats during learned movements [2]. These initial studies have shown that intracortical neuron recordings can indicate the nature of a movement and its direction. These studies do not revel whether the same patterns will be present when the real movements are not made. In that regard, Taylor and Schwartz [2] experimented with rhesus macaques, which made real and virtual arm movements in a computer, the results suggested that the same patterns persisted. The most recent studies with monkeys investigated the control of prosthetic devices for direct real-time interaction with the physical environment [2].

With regard to the application of intracortical neuron recording in BCI systems, microelectrode arrays such as Utah Intracortical Electrode Array (UIEA) have been reported as a suitable means of providing as a suitable means of providing simultaneous and proportional control of a large number of external devices. Kennedy et al. employed cortical control signals to design a BCI that allowed users to control cursor movement and flexion of a cyber-digit finger on a virtual hand [2].

Functional Magnetic Resonance Imaging (fMRI)

fMRI is a non-invasive neuroimaging technique that detects changes in local cerebral blood volume, cerebral blood flow and oxygenation levels during neural activation by means of electromagnetic fields. fMRI is generally performed using MRI scanners which apply electromagnetic fields of strength in the order of 3T or 7T. High space is the main advantage of the use of fMRI. For that reason, fMRI has been applied for localizing active regions inside the brain. However, fMRI has a low temporal resolution of about 1 or 2 seconds. In addition to this, hemodynamic response introduces a physiological delay from 3 to 6 seconds. fMRI appears unsuitable for rapid communication in BCI systems, and is highly susceptible to head motion artifacts.

In BCI systems, fMRI is typically used to measure the Blood Oxygen Level Dependent (BOLD) during neuronal activation [2]. Although the BOLD signal is not directly related to neuronal activity, a correspondence between both does exist. The use of fMRI in BCI technology is relatively recent. Before the development of real-time fMRI, brain activity recording by fMRI has traditionally taken a long time. The data acquired by fMRI techniques were processed offline and the results only became available after several hours or even days. fMRI-based BCIs have been made possible, due to the development of real-time fMRI. The information transfer rate in fMRI-based BCIs is between 0.60 and 1.20 bits/min. Non-clinical fMRI applications are not expected because fMRI requires overly bulky and expensive hardware [2].

Near Infrared Spectroscopy (NIRS)

NIRS is an optical spectroscopy method that employs infrared light to characterize noninvasively acquired fluctuations in cerebral metabolism during neural activity. Infrared light penetrated the skull to a depth of approximately 1-3 cm below its surface, where the intensity of the attenuated light allows alterations in oxyhemoglobin and deoxyhemoglobin concentrations to be measured. Light penetration in the brain is shallow; as a result this optical neuroimaging technique is limited to the other cortical layer. Similar to fMRI, one of the significant limitations of NIRS is the nature of the hemodynamic response changes occur a certain number of seconds after its associated neural activity [2]. The spatial resolution of NIRS is 1 cm, which is quite low. However, NIRS offers low costs, high portability and an acceptable temporal resolution in the order of 100 milliseconds [2].

A NIRS system consists of a light source, a driving electronic device, a light detector, signal processing devices and a recording device. The light source is an infrared emitting diode (IRED) placed in direct contact with the scalp. The driving electronic device is an electronic circuit that controls the IRED in order to modulate the light. The light detector is a photodiode placed right next to the light source. The signal-processing devices are amplifiers and filter that process the electrical signal, and reduce the noise due to ambient light. The recording device is a computer, or any other device that digitalizes, stores and displays the electrical signal.

Ensuring good coupling light from the optical sources and detectors to and from the subjects' head is not a trivial issue. Performance and signal quality can be worsen by head motions or hair obstruction. Good quality signals and noise reduction, especially background noise induced by head motions, are important requirements in real time BCI systems. Hair obstruction can be overcome by combing the hair out of the photons' path by means of hair gel and hair clips. Noise can be reduced partially by bandpass filtering, moving averages and Wiener filtering. These classes of algorithms usually fail to remove abrupt spike-like noise produced by head motion. Ensuring rigid optode positions can minimize head motion artifacts. Solutions have been introduced that are based on helmets, thermoplastic forms, and fibers embedded in neoprene rubber forms. Exploiting the strong statistical association between oxygenated and deoxygenated hemoglobin dynamics can also attenuate background noise effects [2].

NIRS is a relatively new measurement modality, however NIRS promises to be a potent neuroimaging modality for future applicability to BCIs. Currently, NIRS provides a low information transfer rate of about 4bits/min but this transfer rate will increase in the future. NIRS may also be a good alternative to EEG, neither conductive gel nor corrosive electrodes are required. Nevertheless, communication speeds in NIRS-based BCIs are limited due to the inherent delays of the hemodynamic response. Some studies have already demonstrated the feasibility of mental task detection through NIRS-derived optical responses [2].

Control Signal Types in BCIs

The purpose of a BCI is to interpret user intention by means of monitoring their cerebral activity. Brain signals involve numerous simultaneous phenomena relative to cognitive tasks. Most of them are still incomprehensible, and their origins are unknown. Yet, the physiological phenomena of some brain signals has been decoded in such a way that people may learn to modulate them at will, to enable the BCI systems to interpret their Intentions. These signals are regarded as possible control signals in BCIs.

Numerous studies have been described a vast group of brain signals that might serve as control signals in BCI systems. However, only those control signals employed in current BCI systems will be discussed below: visual evoked potentials, slow cortical potentials, P300 evoked potentials, and sensorimotor rhythms. The signal controls are listed in Table 2, along with some of their main features.

Signal	Physiological phenomena	Number of choices	Training	Information transfer rate
VEP	Brain signal modulations in the visual cortex	High	No	60-100 bits/min
SCP	Slow voltages shift in the brain signals	Low (2 or 4, very difficult)	Yes	5-12 bits/min
P300	Positive peaks due to infrequent stimulus	High	No	20-25 bits/min
Sensorimotor rhythms	Modulations in sensorimotor rhythms synchronized to motor activities	Low (2,3,4,5)	Yes	3-35 bits/min

Table 2: Summary of control signals [2]

Visual Evoked Potentials (VEPs)

Brain activity modulations that occur in the visual cortex after receiving a visual stimulus are VEPs. These modulations are relatively easy to detect, the amplitude of VEPs increases enormously as the stimulus is moved closer to the central visual field. VEPs can be classified according to three different criteria: (i) by the morphology of the optical stimuli, (ii) by the frequency of visual stimulation, and (iii) by field stimulation. According to the first criterion, using flash stimulation may cause VEPs, or using graphic patters such as checkerboard lattice, gate and random-dot map. In relation to frequency, VEPs can also be classified as transient VEPs (TVEPs) and steady-state VEPs (SSVEPs). TVEPs occur when the frequency of visual stimulation is below 6 Hz, while SSVEPs occur in reaction to stimuli of a higher frequency. According to the third criterion, VEPs can be divided into whole field VEPs, half field VEPs and part field VEPs, depending upon the area of on-screen stimulus. For illustration, if only half of the screen displays graphics, the other half will not display any visual stimulation, and the person will look at the center of the screen, which will induce a half field VEP [2].

Slow Cortical Potentials (SCPs)

Slow voltage shifts in the EEG that last a second to several seconds are SCPs. SCPs belong to the part of the EEG signals below 1 Hz. Changes in the level of cortical activity are associated with SCPs. Positive SCPs coincide with decreased activity in individual cells, whereas negative SCPs correlate with increased neuronal activity. These brain signals can be self-regulated by both healthy users, and paralyzed patients to control external devices by means of a BCI. SCP shifts can be used to move cursor and select the targets presented on a computer screen [2].

Users can be trained to generate voluntary SCP changes via a thought-translation device. This device is a tool used for self-regulation SCP training, which shows visual-auditory marks so that the user can learn to shift the SCP. The thought-translation device typically comprises of a cursor on a screen in such a way that the vertical position of the cursor constantly reflects the amplitude of SCP shifts. Most thought-translation devices show continuous feedback, yet it is possible to train SCP self-modulation in the absence of continuous feedback [2].

The success in SCP self-regulation training depends on numerous factors, such as the patient's psychological and physical state, motivation, social context or the trainer-patient relationship. It is known that the learning capability of the user drastically affects SCP modulation training. Therefore self-regulation training is strongly recommended for patients at the early stage of a progressive disease. As a result, initial SCP modulation skills have an effect on future performance following training. Consequently, the value of SCPs as a suitable control signal for each patient can only be on determined on a basis of initial trails. There are other factors that have an influence on self-regulation performance, including sleep quality, pain and mood. The effects of these factors are not identical for all patients, and future investigation is certainly needed to establish general rules on this matter.

Self-regulation of SCPs has been tested extensively with patients suffering from ALS. Accuracy rates achieved for SCP classification has typical acceptable accuracy rates varying between 70 and 80 percent, yet the rates of information provided by SCP-based BCI are relatively low. Besides, longer training is required to use SCP-based BCI, and it is likely that users will need continuous practice for several months.

P300 Evoked Potentials

Due to infrequent auditory, visual or somatosensory stimuli, P300 evoked potentials are positive peaks in the EEG. These endogenic P300 responses are elicited about 300 ms after attending to an oddball stimulus among several frequent stimuli. It has been proven in some studies that the less probable the stimulus, the larger the amplitude of the response peak. Usage of P300 based BCIs does not require training. However, the performance may be reduced because the user gets used to the infrequent stimulus, consequently P300 amplitude is decreased [2].

A typical application of a BCI based on visual P300 evoked potentials comprises a matric of letters, numbers or other symbols or commands. The rows or columns of this matrix are flashed at random while the EEG is monitored. The user gazes at the desired symbol and counts how many times the row or column containing the desired choice flashes. P300 is elicited only when the desired row or column flashes, as a result the BCI uses this effect to determine the target symbol. The detection of target symbols from a single trial is very difficult due to the low signal-to-noise ration in EEG signals. The rows or columns must be flashed several times for each choice. The epochs corresponding to each row or column are averaged over the trials in order to improve their accuracy. However, these repetitions decrease the number of choices per minute, for example with 15 repetitions, only two characters are spelled per minute. Auditory stimuli have been used for people with visual impairment; although most of the applications based on P300 evoked potentials employ visual stimuli [2].

P300-based BCIs provide a very low rate of information transmission because the classifier based on an average is too simple, and the accuracy of P300 potential detection is too low. As a result, too many trials are required to select a single symbol in the matrix. The accuracy of P300-based BCIs can be improved, while using a more complicated classifier than a simple average to ensure that the number of repetitions remain unaffected. Studies have proven that the detection accuracy of visual P300 evoked potentials also depends on the properties of the visual matrix such as the dimensions or colors of the symbols. Performance decreases when matrices with smaller symbols are used, and it is enhanced when a green and blue chromatic flicker matrix is used, rather than a gray and black one [2].

Information transmission rates provided by P300-based BCI can be improved by considering the BCI as a noisy transmission system. BCI can therefore benefit from the use of error correcting codes. Conversely, optimizing the code solely according to the maximal minimum Hamming distance implies an increase in target frequency of target stimuli, which might violate physiological constraints leading to difficulties in classifying the individual ERPs, due to overlap and refractory effects. Further overlap and refractory effects are generally the main error source in these kinds of BCIs. Some recent novel approaches have tired to reduce them, by superimposing the targets on a checkerboard or by using alternative stimulus type methods based on motion [2].

The P300 response is not markedly affected by whether or not the subject gazes directly at the target, in contrast to the VEP response, which is larger when the target is foveated. In clinical applications this distinction is important because eye movements are often impaired or lost in the target population. Yet, the performance of a P300-based BCI is substantially improved when subjects gaze at the desired item. Therefore, the performance of the visual P300-based BCIs depends not only on the P300-evoked potential, but also on the VEP response that in turn strongly depends on eye-gaze direction [2].

Sensorimotor Rhythms

Sensorimotor rhythms comprise of mu and beta rhythms, which are oscillations in the brain activity localized in the mu band (7-13 Hz), also known as the Rolandic band and beta band (13-30 Hz) respectively. Both rhythms are connected in such a way that some beta rhythms are harmonic mu rhythms, although some beta rhythms may also be independent. While no actual movement is required to modulate the amplitude of sensorimotor rhythms, the amplitude of the sensorimotor rhythms varies when cerebral activity is related to any motor task. Similar modulation patterns in the motor rhythms are produced as a result of mental rehearsal of a motor act without any overt motor output. Due to the recognition that people can learn to generate these modulations voluntarily in the sensorimotor rhythms, sensorimotor rhythms have been used to control BCIs.

Sensorimotor rhythms can sustain two kinds of amplitude modulations known as event-related desynchronization (ERD) and event-related synchronization (ERS) that are generated sensory stimulation, motor behavior, and mental imagery. ERD engages an amplitude suppression of the rhythm and ERS implies amplitude enhancement. The left panel of Figure 1 shows the temporal behavior of ERD and EFS during a voluntary movement experiment which involved brisk finger lifting. The mu band ERD starts 2.5s before movement on-set, reaches the maximal ERD shortly after movement-onset, and recovers its original level within a few seconds. In contrast, the beta rhythm shows a short ERD during the movement initiation of movement, followed by ERS that reaches the maximum after movement execution. The ERS occurs while the mu rhythm is still attenuated. Figure 1 also shows the gamma oscillation (36-40 Hz), which is another rhythm related to motor tasks as well. Gamma rhythms reveal an ERS shortly before movement-onset, the right panel of Figure 1 illustrates that simultaneous ERD and ERS are possible at different scalp locations [2].

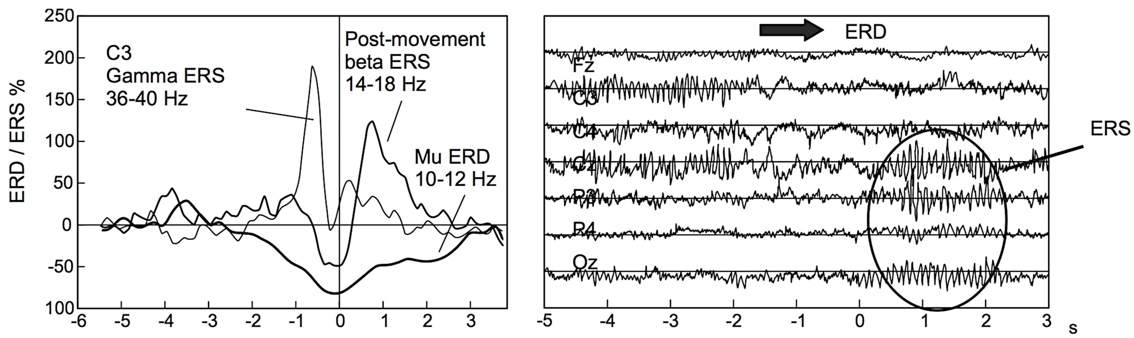

Figure 1: Left Panel Superimposed band power time courses computed for three different frequency bands (10-12 Hz, 14-18 Hz, & 36-40 Hz) from EEG trials recorded from electrode position C3 during right index finger lifting. EEG data triggered with respect to movement-offset. **Right Panel:** Examples of ongoing EEG recorded during right finger movement [2].

Sensorimotor rhythms are related to motor imager without any actual movement. This realization makes if possible to use sensorimotor rhythms for the design of endogenous BCIs, which are more useful than exogenous BCIs. However, self-control of sensorimotor rhythms is not easy, and most people have difficulties with motor imagery. People tend to imagine visual images of related real movements, which is not sufficiently useful for a BCI system, because the patterns of these sensorimotor rhythms differ from actual motor imagery. User training should emphasize kinesthetic experiences, instead of visual representation of actions. Motor imagery training is traditionally based on visual or auditory feedback. This kind of training asks the users to perform a certain motor imagery task, and then the sensorimotor rhythms are extracted and classified by comparing them with a reference [2].

Lastly, visual or auditory feedback is provided to the participant according to the success of the result. This kind of training has been widely used although usually its effectiveness was not very high. Hwang et al. presented more effective motor imagery training based on a system that displayed real-time cortical activity as feedback, which allowed the users to watch their own cortical activity through a real-time monitoring system [2].

Sensorimotor rhythms have been investigated extensively in BCI research. Well-known BCI systems such as Wadsworth, Berlin or Graz BCIs employ sensorimotor rhythms as control signals. The BCIs based on sensorimotor rhythms can operate in either synchronous or asynchronous mode. The latest advances in the field of BCIs based on sensorimotor rhythms have shown that it is possible to predict human voluntary movements before they occur based on the modulations in sensorimotor rhythms. Additionally, this prediction could be provided without the user making any movements at all [2].

Types of BCIs

The BCIs can be categorized into (i) exogenous or endogenous and (ii) synchronous (cue-paced) or asynchronous (self-paced). Types of BCI are listed in Tables 3 and 4, along with information related to brain signals that can be modulated to convey information as well as the advantages and disadvantages. The BCIs can also be classified into dependent and independent. Advantages and disadvantages in both taxonomies are comparable [2].

Approach	Brain signals	Advantages	Disadvantages
Exogenous BCI	-SSVEP -P300	-Minimal training -Control signal set-up easily & quickly -High bit rate (60 bits/min) -Only one EEG channel required	-Permanent attention to external stimuli -May cause tiredness in some users
Endogenous BCI	-SCPs -Sensorimotor rhythms	-Independent of any stimulation -Can be operated at free will -Useful for user with sensory organs affected -Suitable for cursor control applications	-Very time-consuming training (months or weeks) -Not all users are able to obtain control -Multichannel EEG recording required for good performance -Lower bit rate (20-30 bits/min)

Table 3: Main differences between exogenous and endogenous BCI [2].

Approach	Advantages	Disadvantages
Synchronous BCI	-Simpler design and performance evaluation -The user can avoid generating artifacts since they can perform blinks and	-Does not offer a more natural mode of interaction

	other eye movements when brain signals are not analyzed	
Asynchronous BCI	-No requirements to wait for external cues -Offers a more natural mode of interaction	-Much more complicate design -More difficult evaluation

Table 4: Main difference between synchronous & asynchronous BCIs [2].

BCI systems can be classified as either exogenous or endogenous according to the nature of the signals used as input. Exogenous BCI uses the neuron activity elicited in the brain by an external stimulus such as VEPs or auditory evoked potentials. Exogenous systems do not require extensive training since their control signals, SSVEPs and P300, can be easily and quickly set-up. The signal controls can be realized with only one EEG channel and can achieve a high information transfer rate of up to 60 bits /min. Contrarily, endogenous BCI is based on self-regulation of brain rhythms and potentials without external stimuli. Through neurofeedback training, the users learn to generate specific brain patterns, which may be decoded by the BCI such as modulations in the sensorimotor rhythms or the SCPs. The advantage of an endogenous BCI is that the user can operate the BCI at free will, and move the cursor to any point in a two-dimensional space, while an exogenous BCI may constrain the user to the choices presented. Endogenous BCI are also especially useful for users with advanced stages of ALS, or whose sensory organs are affected. Table 3 summarized the differences between exogenous and endogenous BCIs [2].

BCI systems can be classified as synchronous or asynchronous according to the input data processing modality. Synchronous BCIs analyze brain signals during predefined time windows. Any brain signal outside the predefined window is ignored. Consequently, the user is only allowed to send commands during specific periods determined by the BCI system. For illustration, the standard Graz BCI [2] represents a synchronous BCI system. The advantage of a synchronous BCI system is that the onset of mental activity is known in advance and associated with a specific cue. Furthermore, the patients may also perform blinks and other eye movement, which would generate artifacts, if the BCI did not analyze the brain signals to avoid their misleading effects. This insight simplifies the design and evaluation of synchronous BCI. Asynchronous BCIs continuously analyze brain signals no matter when the user acts. They offer a more natural mode of human-machine interaction than synchronous BCI. However, asynchronous BCIs are more computation demanding, and complex. The differences between synchronous and asynchronous BCIs are summarized in Table 5.

EEG BCI configuration

The EEG recording system consists of electrodes, amplifiers, A/D converter, and a recording device. As the electrodes acquire the signal from the scalp, the amplifiers process the analog signal to enlarge the amplitude of the EEG signals so that the A/D converter can digitalize the signal in a more accurate way. Lastly, a recording device, such as a personal computer or a similar device stores and displays the data.

The EEG signal is measured as the potential difference over time between signal or active electrode and reference electrode. An extra electrode, know as the ground electrode, is used to measure the difference between the active and the reference points. The minimal configuration for EEG measurement therefore consists of one active and the reference points. The minimal configuration for EEG measurement therefore consists of one active, one reference, and one ground electrode. Multi-channel configurations can comprise of up to 128 or 256 active electrodes. These electrodes are typically made of silver chloride (AgCI) [2]. Electrode-scalp contact impedance should be between 1kΩ to 10Ω to record accurate signal. The electrode-tissue interface is not only resistive but also capacitive and it therefore behaves as a low pass filter. The impedance depends on several factors such as the interface layer, electrode surface area, and temperature. EEG gel creates a conductive path between the skin and each electrode that reduces the impedance. Use of the gel is cumbersome, however, as continued maintenance is required to assure a relatively good quality signal. Electrodes that do not need the use of gels, called "dry" electrodes, have been made with other materials such as titanium and stainless-steal. These kinds of electrodes may be "dry" active electrodes, which have preamplification circuits for dealing with high electrode/skin interfacial impedances, or "dry" passive electrodes, which have no active circuits, but are linked to EEG recording systems with ultra-high input impedance [2].

The amplitude of electrical bio-signals is in the order of microvolts. As a result, the signal is very sensitive to electronic noise. External sources such as power-lines may generate background noise and thermal, shot, flicker, and burst noises are generated by internal sources [2]. Design consideration should be addressed to reduce the effects of the noise, such as electromagnetic interference shielding or reduction for common mode signal, amongst others [2].

As previously discussed, EEG is recorded by electrodes. The electrodes placed over the scalp are commonly based on the International 10-20 system, which has been standardized by the American Electroencephalographic Society. The 10-20 system uses two reference points in the head to define the electrode location. The nasion is one of these reference points, which is located at the top of the nose at the same level as the eyes. The inion is the other reference point, which is located at the base of the skull (Figure 1)[2].

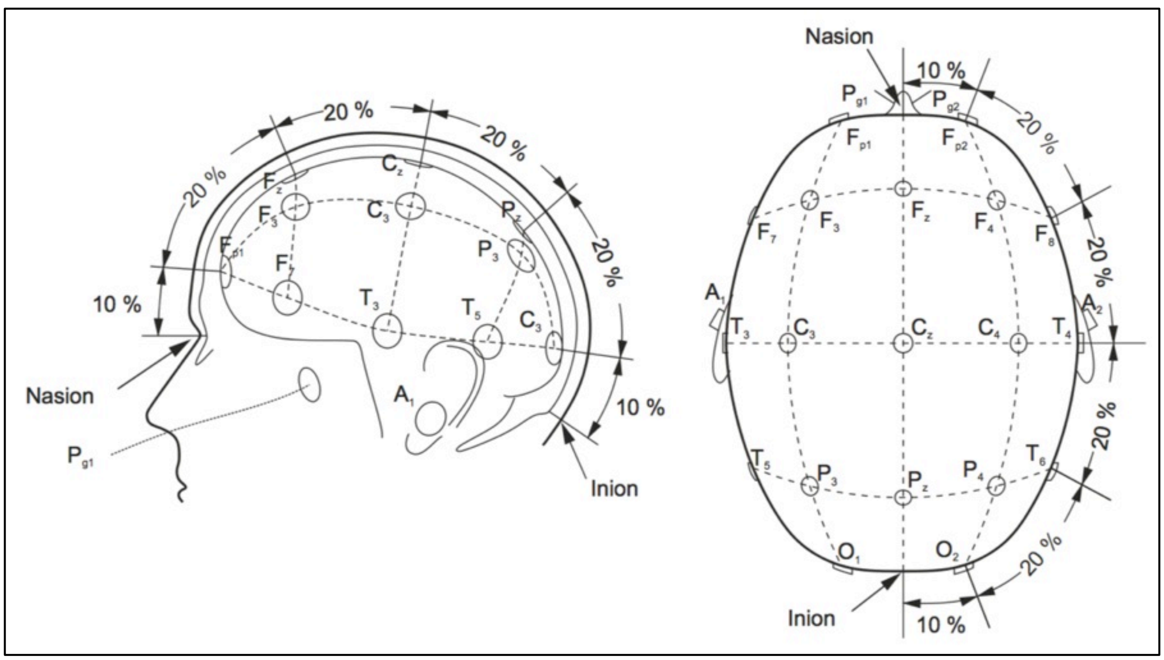

Figure 2: Electrode placement over scalp [2]

The transverse and median planes divide the skull from these two points. The electrode locations are determined by marking these planes at intervals of 10% and 20%. The letters in each location corresponds to specific brain regions in such a way that A represents the ear lobe, C the central region, P_g the nasopharyngeal, P the parietal, F the frontal, F_P the frontal polar and O the occipital area [2].

EEG signals

EEG comprises a set of signals that may be classified according to their frequency. Well-know frequency ranges have been defined according to distribution over the scalp or biological significance. These frequency bands are referred to as delta (δ), theta (θ), alpha (α), beta (β), and gamma (γ) from low to high, respectively. The relevant characteristics of these bands are detailed below.

Delta Band

The delta band lies below 4 Hz, and the amplitude of delta signals detected in babies decreases as they age. Delta rhythms are usually only observed in adults in deep sleep state and are unusual in adults in an awake state. A large amount of delta activity in awake adults is abnormal and is related to neurological diseases [2]. Due to its low frequency, it is easy to confuse delta waves with artifact signals, which are caused by the large muscles of the neck or jaw.

Theta Waves

Theta waves lie within the 4 to 7 Hz range. In a normal awake adult, only a small amount of theta frequencies can be recorded. Larger amounts of theta frequencies can be seen in young children, older children, and adults in drowsy, meditative or sleep states [2]. Similar to delta waves, a large amount of theta activity in awake adults is related to neurological disease [2]. Theta band has been associated wit meditative concentration [2] and a wide range of cognitive processes such as mental calculation, maze task demands, or conscious awareness [2]. In the Sternberg memory scanning task [3], experimental subjects were given a set of items to remember such as letters 'd', 'g', and 'z' and after a short delay, were asked to say whether or not a probe item, such as 'a' was among the items in the memory set [1]. The time that it took subjects to respond in this task typically increased linearly with the number of items in the memory set. This model accounted for the linear increases with memory set size of the mean, variance and skewness of response times, and for the faster responding for items most recently entered into the memory set when the list-probe delay is short. Both iEEG and MEG have revealed evidence that theta power increases during the performance of the Sternberg task, more so the greater the memory load. A MEG study performed by Jensen and Tesche [1][4] found that theta power in the frontal cortex increased during all phases, encoding, retention and scanning, contrary to the iEEG study performed by Raghavachari [5] which found an increase in theta power only during encoding and retention, while decreasing during scanning [1]. It must be noted that different neurons were monitored in the two studies, the iEEG electrodes were distributed in grids over various regions of cortical surface, these results indicate that theta oscillations might play different roles in different cortical areas. A potential explanation is that several different memory processes interact by phase locking their theta and other rhythms to communicate results and commands [1]. The results of the Raghavachari study is supported by another IEEG study performed by Halgren [6] that found increased phase locking (but decreased theta power) in the theta and alpha frequency bands between various distant sites in the brain during a difficult working memory task, suggestive of the interactions of a central executive process with an occipital visual scratch pad, an articulatory loop and a limbic monitor [1]. There are challenges that remain for the gamma/theta model of short-term memory, both in terms of further developing the model to account for additional empirical facts about short-term memory. Alternative models, such as the one presented by Townsend and Ashby [7] may do better with other memory facts and in terms of the functional anatomy of the brain regions associated with short-term memory such as frontal and temporal areas. However, the gamma/theta model presented by Sternberg show that it is theoretically possible to bring brain oscillatory processes into close correspondence with dynamic memory processes [1].

Theta in memory encoding

Theta oscillations are seldom seen directly in EEG recording from humans, this occurrence has been difficult to understand what the classically observed increases in theta power meant. Recently, intracranial EEG (iEEG) recordings from epileptic patients have revealed strong theta oscillations from many areas of the human brain. From these experiments, it was show that periods in which theta oscillations were apparent were more frequent when patients were navigating through a virtual maze by memory alone, when compared to when they were guided through the maze by arrow cues. The theta periods were longer the longer the maze. However, theta did not covary with the time taken to make decision at choice points, rather gamma oscillations were more prevalent the longer the decision time. Consequently, theta oscillations are more closely linked to encoding and retrieval in memory than they are to other cognitive processes [1].

Alpha Rhythms

Alpha rhythms are found over the occipital region in the brain [2]. These waves lie within the 8 to 12 Hz range. Their amplitude increases when the eyes close and the body relaxes and they attenuate when the eyes open and mental effort is made [2]. These rhythms primarily reflect visual processing in the occipital brain region and may also be related to the memory brain function [2]. There is also evidence that alpha activity may be associated with mental effort. Increasing mental effort causes a suppression of alpha activity, particularly from the frontal areas [2]. Consequently, these rhythms might be useful signals to measure mental effort. Mu rhythms may be found in the same range as alpha rhythms, although there are important physiological differences between both. In contrast to alpha rhythms, mu rhythms are strongly connected to motor activities and in some cases, appear to correlate with beta rhythms [2]. There is a notion that alpha synchronization indexes 'cortical idling', but it is becoming apparent that alpha oscillations indicate that attention is actively suppressing cortical activity related to distractors as a part of the process of focusing attention on important targets [1]. An illustration of this is evident in the Sternberg memory-scanning task [8], alpha power increased with memory load, reflecting a need to suppress distraction. A study by Cooper [9] indicated that attention is directed internally towards metal imagery, alpha power at attention-relevant scalp sties is greater than during externally-directed, information-intake tasks, reflecting suppression of external input during the imagery task [9][1]. The Cooper study also showed that when external task load increased, alpha power increased, reflecting the need to suppress competing information sources [1]. Changes in alpha power has been attributed to the anticipation of attentional demands, such as when a cue indicating an upcoming auditory stimulus induced increased alpha power over parieto-occipital (visual) cortex compared with when the cue indicated an upcoming visual stimulus [1]. When the task was purely visual, the changes occurred precisely over visual cortical areas where neural activity representing distractions in the visual field is likely to occur [1]. An noteworthy observation is induced alpha power decreased over the entire scalp (~300-700ms) after attended visual stimuli appeared in comparison with when unattended stimuli appeared, whereas beta power (~16Hz) increased around 600 ms after the stimulus occurred [1]. This decrease in alpha power occurred concurrently as gamma power increased, possibly representing temporal binding of visual features [1], suggesting that gamma synchronization for feature binding might require alpha desynchronization.

Beta Rhythms

Beta rhythms, that are within the 12 to 30 Hz range, are recorded in the frontal and central regions of the brain and are associated with motor activities. Beta rhythms are desynchronized during real movement or motor imagery [2]. Beta waves are characterized by their symmetrical distribution when there is no motor activity. Conversely, in case of active movement, the beta waves attenuate, and their symmetrical distribution changes [2].

Gamma rhythms

Gamma rhythms are in the frequency range from 30 to 100 Hz. The presence of gamma waves in the brain activity of a healthy adult is related to certain motor functions or perceptions, among others [2]. A number of experiments have shown a relationship in normal humans between motor activities and gamma waves during maximal muscle contraction [2]. This gamma band coherence is replaced by a beta band coherence during weak contractions, which suggests a correlation between gamma or beta cortical oscillatory activity and force [2]. Additionally, several studies have provided evidence for the role of gamma activity in the perception of both visual and auditory stimuli [2] Gamma rhythms are less commonly used in EEG-based BCI systems, due to artifacts such as electromyography (EMG) or electrooculography (EOG) are likely to affect them [2]. Nevertheless, this range is attracting growing attention in BCI research due to the comparison to traditional beta and alpha signals, gamma activity may increase the information transfer rate and offer higher spatial specifity [2]. Gamma frequency has been reported to have correlations between conscious awareness and synchronous neural activity at various frequencies. In 1993, Crick and Koch suggested that synchronous neural firing at the gamma frequency might be the neural correlate of visual awareness [1]. Since then there have been several important studies that reported correlations between conscious awareness and synchronous neural activity at various frequencies. In a study performed by Eugenio Rodriguez, EEG recorded while subjects viewed an ambiguous visual stimulus that could be perceived as either a face or as a meaningless shape. When the subjects reported seeing a face, a phase synchronization at the gamma frequency occurred across widely separated brain areas, while this synchronization did not appear when a meaningless pattern was reported [10]. Figure 2 shows idealized power spectra, showing peaks at canonical EEG frequencies. While any of the frequencies can occur at any electrode site, alpha power modulations are often recorded at posterior sites, theta at frontal sites and gamma over sensory cortices [1].

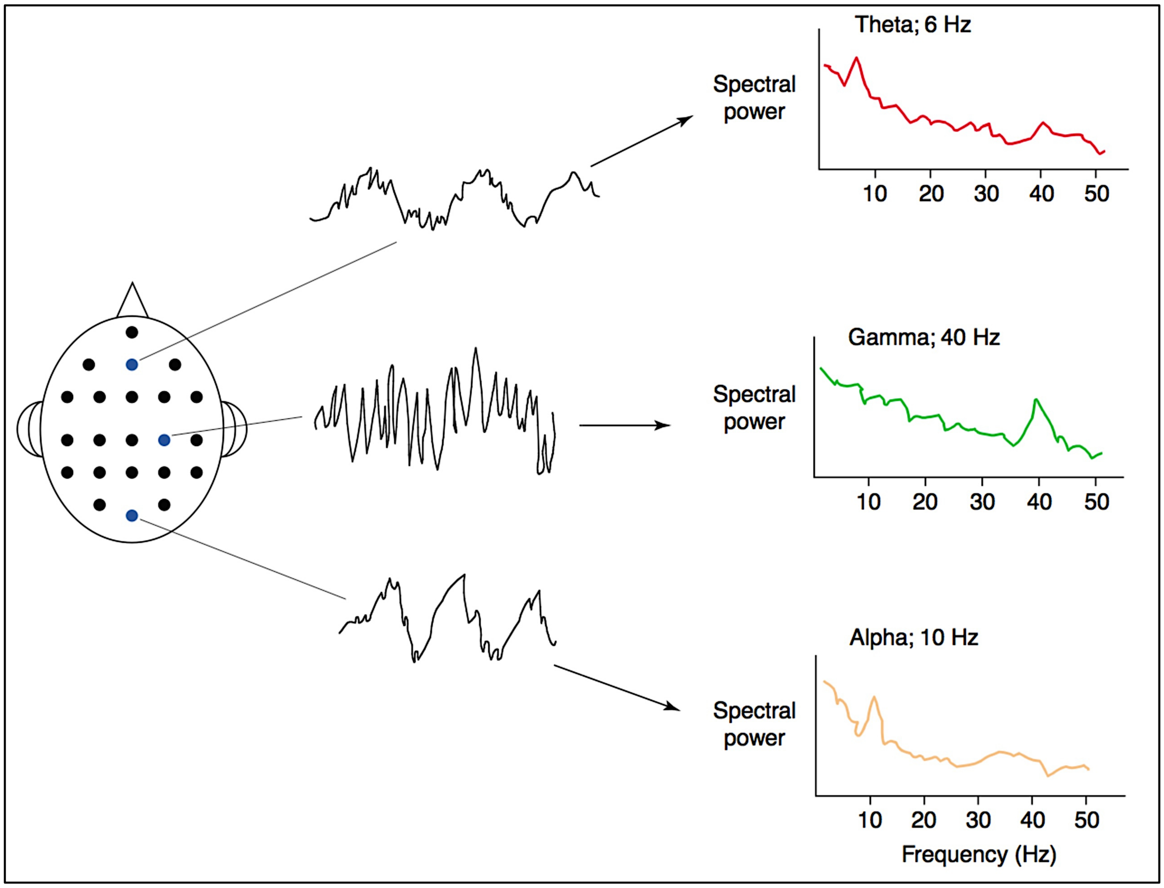

Figure 3: Some idealized power spectra showing peaks at canonical EEG frequencies. While any of the frequencies can occur at any electrode site, alpha power modulations are often recorded at posterior sites, theta at frontal sites, and gamma over sensory cortices [1].

EEG oscillations and cognitive processes

The output of EEG activity varies in both humans and animals, particularly the sleep-wakefulness cycle. Spectral power, which is measured in power per unit area per unit wavelength, changes with age at various frequencies changes. Alpha power increases as children mature, whereas theta and delta power decreases. These changes are linked to a more general increase in cognitive competence with maturation, whereas the reverse changes signals declining metal abilities due to old age. Alpha waves have been evident in EEG recordings since the invention of electroencephalography by Han Berger during the 1930's. Alpha power is larger when the eyes are closed rather than open, as a result the conventional wisdom was that alpha power reflected a relaxed unoccupied brain. An overall decrease in alpha power has been linked to increasing demand of attention, alertness and task load in general. In contrast to alpha power, theta power tends to increase in memory tasks, especially during encoding. These waves have been thought to reflect different cognitive operations occurring in cortico-thalamic circuits, theta for encoding and alpha for search and retrieval [1].

Hemodynamic response

The hemodynamic response is the process of blood releasing glucose to active neurons at the greater rate than in the area of inactive neurons. The result of this process is glucose and oxygen being delivered through the blood stream resulting in a surplus of oxyhemoglobin in the veins of the active area, and a distinguishable change of the local ratio of oxyhemoglobin to deoxyhemoglobin [2]. These changes can be quantified by neuroimaging methods such as functional magnetic resonance and near infrared spectroscopy. Functional magnetic response and near infrared spectroscopy are categorized as indirect because they measure hemodynamic response, which in contrast to electrophysiological activity, is not directly related to neuronal activity [2].

Challenges of BCI

Artifacts in BCIs

Artifacts are undesirable signals that contaminate brain activity, and are mostly of non-cerebral origin. Artifacts may reduce the performance of BCI-based systems due to the shape of neurological phenomenon being affected. Artifacts may be classified into two major categories: physiological artifacts and non-physiological or technical artifacts [2].

Physiological artifacts are usually due to muscular, ocular and heart activity, known as electromyography (EMG), electrooculography (EOG), and electrocardiography (ECG) artifacts respectively. EMG artifacts typically imply large disturbances in brain signals, due to electrical activity caused by muscle contractions, which occur when patients are talking, chewing or swallowing. Blinking and other eye movements produce EOG artifacts. Blinking generally makes high-amplitude patterns over brain signals in contrast to eye movements that produce low-frequency patterns. These electrical patterns are due to the potential difference between the cornea and the retina, as their respective charges are positive and negative. Due to this realization, the electric field around the eye changes when this dipole moves. EOG artifacts mostly affect the frontal area; they are approximately attenuated according to the square of the distance. Lastly, ECG artifacts, which reflect heart activity, introduce a rhythmic signal into brain activity [2].

Technical artifacts are mainly attributed to power-line noises or changes in electrode impendences, which can usually be avoided by proper filtering or shielding. Consequently, the BCI community focuses principally on physiological artifacts, given that their reduction during brain activity acquisition is a much more challenging issue than non-physiological artifact handling [2].

There are several ways of handling physiological artifacts found in literature. Artifacts may be avoided, rejected or removed from recordings of brain signals. Artifact avoidance involves asking patients to avoid blinking or moving their body during the experiments. This approach to artifact handling is very simple, due to the fact that it does not required any computation, as brain signals are not assumed to have artifacts. Yet, this assumption is not always feasible given that some artifacts including involuntary heat beats, eye and bodily twitches, are not easily avoidable during data recording, especially in cases of strong neurological disorders. Artifact rejection approaches suggest discarding the epoch contaminated by the artifacts. Manual artifact rejection is an option to remove artifacts in brain signals and an expert could identify and eliminate all artifact-contaminated epochs. The main disadvantage in using manual rejection is that it requires intensive human labor, and this approach is not suitable for on-line BCI systems. However, EMG and EOG artifact detection can perform this task automatically. If EMG and EOG signals are monitored, the brain signal samples may be removed whenever ocular or muscular activity of the arms is detected. Automatic rejection is an effective way of handling artifacts, but it may fail when EOG amplitudes are too small. Furthermore, rejection methodology means that the user loses device control when artifact contaminated signals are discarded. Rather than rejecting samples, the artifact removal approach attempts to identify and remove artifacts while keeping the neurological phenomenon intact. Common methods for removing artifacts in EEG are linear filtering, linear combination and regression, BSS and PCA.

Research

BCI technology has not been the subject of extensive scientific investigation. The idea of successfully deciphering thoughts or intentions via brain activity is vied as strange and remote in the past. As a result, research in the field of cerebrum activity has been limited to the clinical and laboratory analysis of neurological disorders. The design of BCI was considered too complex due to the limited resolution and reliability of information that was detectable in the cerebrum, which has high variability. Compounding these challenges is the realization that BCI systems require real-time signal processing, therefore until recently the requisite technology was either extremely expensive, or simply did not exist. BCI research remains a relatively young field that integrates neuroscience, physiology, psychology, engineering and computer science. As a result of the infancy of this field, notable advance and a common language has yet to emerge, existing BCI technologies varies making their comparison difficult slowing down research as a result.

Neurophysiology

Discussion

References

Apa style

[1] Ward, Lawrence M. (2003). Synchronous Neural Oscillations and Cognitive Processes. *Trends, 7*(12), 7.

[2] Luis Fernando Nicolas-Alonso, Jamie Gomez-Gil. (2012). Brain Computer Interfaces, a Review. *Sensors*, 70.

[3] Jensen, O. and Lisman, J.E. (1998) An oscillatory short-term memory buffer model can account for data on the Sternberg task. J. Neurosci. 18, 10688–10699

[4] Jensen, O. and Tesche, C.D. (2002) Frontal theta activity in humans increases with memory load in a working memory task. Eur. J. Neurosci. 15, 1395–1399

[5] Raghavachari, S. et al. (2001) Gating of human theta oscillations by a working memory task. J. Neurosci. 21, 3175–3183

[6] Halgren, E. et al. (2002) Rapid distributed fronto-parietal-occipital processing stages during working memory in humans. 710–728

[7] Townsend, J.T. and Ashby, F.G. (1983) Stochastic Modeling of Elementary Psychological Processes, Cambridge University Press

[8] Jensen, O. et al. (2002) Oscillations in the alpha band (9–12Hz) increase with memory load during retention in a short-term memory task. 877–882

[9] Cooper, N. et al. (2003) Paradox lost? Exploring the role of alpha oscillations during externally vs. internally directed attention and the implications for idling and inhibition hypotheses. Int. J. Psychophysiol. 47, 65–74

[10] Eugenio Rodriguez, Nathalie George, Jean-Philippe Lachaux, Jacques Martinerie, Bernard Renault, Francisco J. Varela. (1999). Perception's shadow: long-distance synchronization of human brain activity. *Nature, 397*, 4.

[11] Naresh Khatri, Alvine H. Ng. (2000). The Role of Intuition in Strategic Decision Making. *Human Relations, 53*(1), 57.

Appendices

<u>Terms</u>

Oxyhemoglobin

Deoxyhemoglobin

Brain areas

Background noise