A PORTABLE AND EMBEDDED SSVEP BCI SYSTEM: emBCI

(TAŞINABİLİR VE GÖMÜLÜ BİR SSVEP BBA SİSTEMİ: emBCI)

by

Ozan ÇAĞLAYAN, B.S.

Thesis

Submitted in Partial Fulfillment

of the Requirements

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"Our hearts shall wither if we ever forget."

"Wake up Berkin Elvan."

January 2014, Istanbul

Ozan Çağlayan

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List of Abbreviations

ALS Amyotrophic Lateral Sclerosis

AP Action Potential

AR Autoregressive

BBB BeagleBone Black

BCI Brain-Computer Interface

BMI Brain-Machine Interface

CNS Central Nervous System

DBI Direct Brain Interface

ECoG Electrocorticography

EEG Electroencephalography

ERP Event-Related Potential

fMRI Functional Magnetic Resonance Imaging

fNIRS Functional Near-Infrared Spectroscopy

GUI Graphical User Interface

HCI Human-Computer Interaction

LIS Locked-in Syndrome

M1 Primary Motor Cortex

MEG Magnetoencephalography

MI Motor Imagery

OS Operating System

PNS Peripheral Nervous System

PRU Programmable Realtime Unit

PSD Power Spectral Density

SCP Slow Cortical Potentials

SMR Sensorimotor Rhythms

SNR Signal-to-Noise Ratio

SSVEP Steady-State Visual Evoked Potential

V1 Primary Visual Cortex

VEP Visual Evoked Potential

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Abstract

The objective of a brain-computer interface (BCI) is to provide an alternative way of interaction between the brain and the environment without the involvement of muscular pathways. Besides being a revolutionary human computer interface for gaming and entertainment, BCIs constitute the only way of interaction/communication with the outer world for people who cannot voluntarily control/move their muscles.

Electroencephalography (EEG) is a non-invasive method for measuring the electrical activity generated within the brain structures, through the scalp. Although new consumer grade, wireless, portable and battery-powered EEG headsets are recently gaining popularity, most of the non-invasive BCI research depends on high quality but bulky and expensive EEG acquisition systems. Combined with a decent PC to implement the software stack of the BCI, the cost of the overall BCI design increases and the technology quickly becomes unaffordable for many people.

In this study, we present a portable and embedded steady-state visual evoked potential BCI system in which the user can choose between two targets by focusing on 2 LED matrices flickering at different frequencies. The output of the system can then be used for different interaction scenarios like controlling a robot, answering simple yes/no questions, etc. The use of a consumer grade, wireless EEG headset together with a cheap embedded computer increases the mobility of the system while reducing the overall cost dramatically.

Résumé

L'objectif d'une interface cerveau-ordinateur (ICO) est de fournir un moyen alternatif d'interaction entre le cerveau et l'environnement sans la participation des voies musculaires. En plus d'être une interface homme-machine révolutionnaire pour les jeux et l'amusement, les ICO constituent la seule moyenne d'interaction et de communication avec le monde extérieur pour les personnes qui ne peuvent pas contrôler/déplacer leurs muscles volontairement.

L'électroencéphalographie (EEG) est une méthode non-invasive pour mesurer l'activité électrique générée à l'intérieur des structures du cerveau, à travers le cuir chevelu. Bien que nouveaux casques EEG portables et sans fil gagnent en popularité récemment, la plupart des recherches sur les ICO non-invasives utilise des systèmes d'acquisition EEG encombrants et coûteux de haute qualité. En combinaison avec un bon ordinateur pour mettre en œuvre la pile logicielle des ICO, le coût de la conception augmente et la technologie devient vite inaffordable pour beaucoup de gens.

Dans cette étude, nous présentons une ICO réalisée avec un système embarqué dans laquelle l'utilisateur peut choisir entre deux cibles en se concentrant sur deux matrices de LED avec différentes fréquences de clignotement. La sortie du système peut alors être utilisé pour différents scénarios d'interaction comme commander un robot, répondre à des questions simples oui/non, etc. L'utilisation d'une casque EEG sans fil avec un ordinateur embarqué pas cher augmente la mobilité du système en réduisant considérablement le coût total.

Özet

Beyin-bilgisayar arayüzlerinin (BBA) amacı, beyin ve dış dünya arasında, kasların kullanılmadığı alternatif bir etkileşim yöntemi sunmaktır. Oyun ve eğlence dünyası için devrim niteliğinde bir insan-makine arayüzü olmasının yanı sıra, BBA sistemleri hiçbir istemli kasını hareket ettiremeyen ancak beyinleri sağlıklı olan insanların, dış dünya ile iletişime geçmelerinin tek yoludur.

Elektroensefalografi (EEG) kafatası derisi üzerinden beynin elektriksel etkinliğini ölçmek için kullanılan, girişimsel olmayan (non-invaziv) bir görüntüleme tekniğidir. Son kullanıcı pazarını hedefleyen, kablosuz aktarımı temel alan ve pil ile çalışan ucuz taşınabilir EEG kaskları son zamanlarda iyiden iyiye popülerleşse de, non-invaziv BBA araştırmalarının büyük çoğunluğu hâlen yüksek kaliteli, çok fazla taşınabilir olmayan ve pahalı EEG sistemleriyle yürütülmektedir. Sisteme eklenecek olan iyi bir bilgisayar ile birlikte toplam maliyet çoğu insanın gelir seviyesini aşacak düzeye ulaşmaktadır.

Bu çalışmada, kullanıcının farklı frekanslarda yanıp sönen LED matrislerine odaklanarak iki farklı durumdan birini seçebilecekleri taşınabilir ve gömülü bir BBA tasarımı sunulmaktadır. İki çıkışlı bu BBA, robot kontrolü için veya sorulan sorulara evet/hayır şeklinde cevap verilmesine olanak sağlayacak etkileşim senaryolarında kullanılabilir. Kablosuz, ucuz, taşınabilir ve pilli bir EEG kaskı ile ucuz bir gömülü bilgisayarın bütünleştirildiği bu tasarım, hareket kabiliyetini ve taşınabilirliği arttırırken, toplam maliyeti ciddi bir şekilde düşürmektedir.

1 INTRODUCTION

1.1 Motivation and Objective

Research in Brain-Computer Interface (BCI) design often focuses on discovering novel approaches in experiment protocol design and boosting the performance of signal processing and machine learning algorithms in order to improve the information transfer rate, the ergonomics and the ease of use.

Although measuring brain activity with electroencephalography (EEG) is more comfortable when compared to other measurement methods, clinical and research EEG acquisition systems are still far from being portable: They heavily rely on wired transmission, they are generally not battery-powered and the application of a conductive material between electrodes and the scalp is often necessary to improve the signal quality. Also, the cost of such systems generally exceeds the income level of many people, thus they can not be considered as affordable technologies.

With the advent of technology in communication and electronics, new affordable (less than ~$500) EEG systems started to appear in the market. These consumer grade wireless and battery-powered headsets are equipped with either dry or saline electrodes which simplify the setup process and make the whole experience much more comfortable.

Online (real-time) BCIs generally require good computers as stimuli presentation, data acquisition, signal processing, machine learning and finally production of an output are all resource hungry processes. Some of these processes are also timing sensitive, e.g. the stimuli should be presented at exact intervals, the acquisition should not miss a packet, etc. The progress in computer hardware industry does not always bring the same amount of progression into software components. According to Wirth's Law stated by Niklaus Wirth, *software is getting slower more rapidly than hardware becomes faster* (Wirth, 1995). The fact that operating systems (OS) and their software components are becoming much more sophisticated negatively impacts the precision, the performance and the real-time expectations of dedicated/critical tasks running on a computer. Once the software part of a BCI heavily depends on a general purpose and end-user targeted modern OS, the cost of the overall BCI system increases since the price of the minimum PC (laptop or desktop) configuration adequate for the software stack is ranging between $700-1000.

Embedded computers are small single-board computers designed to satisfy application specific designs, e.g. mobile phones, tablets, robot controllers, etc. The cost for these boards is dramatically reduced with the popularity of smart phones and other ubiquitous appliances. The price for a *Raspberry Pi* equipped with single core 700MHz ARM microprocessor and 256MB of memory is $25 while much more powerful boards in the price range $40-100 are available. These embedded computers are traditionally running with Linux distributions which are open-source software stacks built around the Linux kernel and a plethora of other tools, libraries and utilities. Linux, with its powerful and productive command line abilities, does not depend on the existence of a graphical desktop environment. This allows to dedicate the memory and CPU resources normally wasted by GUIs to other design-specific tasks. The modular nature of Linux allows one to prepare a customized OS image which will directly boot into the BCI software. More aggressive resource optimization can be done by removing unused system services and applications. Each customization step help in reducing overall power consumption of the BCI system, which is key to designing a portable, battery-powered and ubiquitous BCI.

One big challenge in embedded BCI design is to decide which programming language and libraries will be used for data acquisition, signal processing, stimuli presentation and optionally machine learning. This generally is not a big deal for BCIs running on top of conventional PCs as there exists lots of alternatives be it standalone or MATLAB based. The major obstacle in reusing these already available frameworks is that they are all developed, tested and used on x86 CPU architecture and thus are not available for ARM CPU architecture. Although MATLAB has support for generating code for embedded targets, MATLAB itself is a commercial product which can not be accessed free of charge.

Python is a high-level, easy to learn interpreted language with a huge number of extension modules developed by the community. Python is also multi-platform thus it is possible to run Python programs on a wide range of different operating systems and architectures. Another advantage of Python which made it very popular among scientific researchers is the ability to write code that will run as fast as the underlying hardware allows, thanks to scientific Python modules implemented in C like *NumPy* and *SciPy* (Oliphant, 2007).

The objective of this thesis is to assess the feasibility of a low-cost and online BCI design which will be completely driven by an inexpensive embedded computer running BCI software written purely in Python on Linux OS. We believe that application-specific embedded computing with consumer grade EEG headsets will help in increasing the availability of BCIs by reducing the overall cost.

1.2 Thesis Outline

The remainder of this thesis is structured as follows.

In Chapter 2, we briefly introduce the neurophysiological processes behind BCI design along with the brain activity measurement techniques and the cognitive paradigms often used to extract useful information out of the brain.

Chapter 3 presents in detail the materials and methods for the embedded BCI system proposed by this study.

Finally, Chapter 4 concludes what have been achieved by this thesis and discusses further research possibilities about embedded BCI design.

2 BRAIN COMPUTER INTERFACES

The locked-in syndrome (LIS) is a medical condition in which patients are awake and conscious but cannot move or communicate verbally because of complete paralysis of nearly all voluntary muscles. LIS is mostly caused by traumatic brain injuries, brain strokes, hemorrhages, head trauma, demyelinating diseases or infectious conditions. Amyotrophic Lateral Sclerosis (ALS) (Also known as Lou Gehrig's disease, named after a popular baseball player who was diagnosed with ALS in 1939) is a neurodegenerative disease which is one of the major causes of LIS. ALS basically attacks motor neurons that control voluntary muscles in the body. When those motor neurons stops functioning, the muscles lose strength and progressively die (Atrophy). A cure for ALS is currently not available and the cause of the disease is still unknown.

According to ALS Association, nearly 5600 people in the United States are diagnosed with ALS each year and the incidence of the disease is 2 per 100.000 people[1]. Although there doesn't seem to be an incidence study related to ALS in Turkey, it is estimated that 6000-8000 people have the disease.[2].

When consciousness and cortical functions are preserved, it may actually be possible to use healthy brain activity in order to build a novel way of interaction between the subject's brain and the environment using special brain signal acquisition techniques and computers. These composite systems are called Brain-Computer Interfaces (BCI), Brain-Machine Interfaces (BMI) or Direct Brain Interfaces (DBI). BCIs in general have the potential to improve the life quality of disabled people and may actually be the only way of interaction for completely locked-in people.

[1] http://www.alsa.org/about-als/facts-you-should-know.html
[2] http://www.als.org.tr/haber_detay.asp?haberID=77

2.1 Definition of a BCI

According to Wolpaw et al. (2002), a BCI is a communication system in which messages or commands sent to the external world do not pass through the brain's normal neuromuscular output pathways; thus BCIs provide an alternative way for people to act on the world.

Three mandatory elements for a BCI system has further been enumerated by Graimann et al. (2010):

1. A BCI must directly record brain activity,
2. A BCI must provide *realtime* feedback to the user,
3. A BCI must be based on intentional control.

The *intentional control* constraint mentioned above, leaves the devices that detect changes in brain activity occurring without any intent like workload, arousal or sleep, out of the definition for BCIs.

A more application-focused definition from the perspective of Human-Computer Interaction (HCI) proposed by Zander et al. (2010) is as follows:

> *"A BCI is a system to provide computer applications with access to real-time information about cognitive state, on the basis of measured brain activity."*

Zander et al. (2008) also categorized BCIs into three types:

- *Active BCI* A BCI deriving its outputs from consciously controlled brain activity.
- *Reactive BCI* A BCI deriving its outputs from brain activity arising in response to external stimuli.
- *Passive BCI* A BCI deriving its outputs from arbitrary brain activity without the purpose of voluntary control.

According to this categorization, passive BCIs embrace the systems based on arbitrary activity detection which were not previously counted as BCIs by Graimann et al. (2010).

Active and Reactive BCIs are also referred as *endogenous* (self-generated) and *exogenous* (evoked) BCIs in literature (Jackson and Mappus, 2010).

2.2 Neural Principles

2.2.1 Central Nervous System

The central nervous system (CNS) is the part of the nervous system which integrates sensory information it receives from the body and responds to it accordingly. Together with the peripheral nervous system (PNS) which connects CNS to the limbs and organs, it plays an important role in determining the behavior. The two structures that make up the CNS are the brain and the spinal cord which is the information pathway containing nervous tissue that extends from the brain.

The human brain is divided into two (left and right) cerebral hemispheres covered with *cortex* which is also known as the *gray matter*, the type of CNS tissue made of neurons. The hemispheres are connected through a central structure called *corpus callosum* which is a bundle of neural fibers that enables the communication between hemispheres.

Each cerebral hemisphere is further divided into frontal, parietal, occipital and temporal lobes (Figure 2.1) which have specialized functions (Table 2.1) driving our cognitive abilities. It should be noted that each hemisphere is primarily involved in sensory and motor processes on the opposite side of the body and the "apparently" similar cerebral hemispheres are neither functionally equivalent nor exactly symmetrical (Kandel et al., 2013).

Table 2.1: Functional Description of Cerebral Lobes

Frontal Lobe	Executive functions, movement control *(Primary motor cortex (M1))*
Parietal Lobe	Multimodal sensory information integration
Occipital Lobe	Visual processing center containing the *visual cortex (V1)*
Temporal Lobe	Hearing and auditory signal processing, memory, emotion

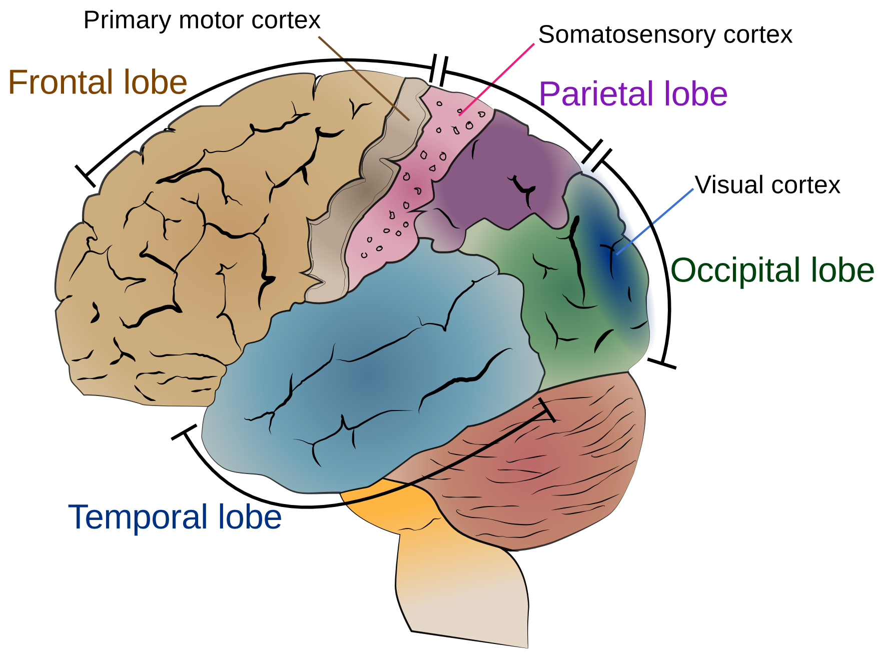


Figure 2.1: Functional Regions of the Cerebral Cortex (Adapted from Wikipedia)

2.2.2 Neurons

Neurons or nerve cells are the core components of the brain. There are approximately 10^{11} neurons in the human brain (Kandel et al., 2013) forming complex interconnected networks to produce human behavior.

A typical neuron is composed of four regions: The cell body or soma, dendrites, axon and presynaptic terminals (Figure 2.2).

The cell body, surrounded by a membrane made of a lipid bilayer, is the center of the neuron containing the nucleus which is responsible for protein synthesis. A number of

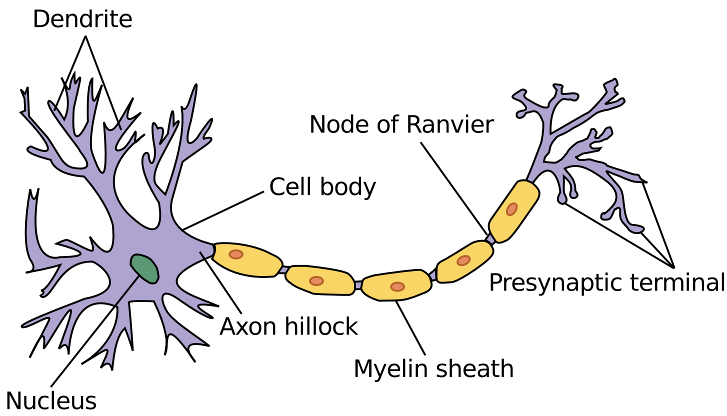


Figure 2.2: The Structure of a Neuron (Adapted from Wikipedia)

short branches called *dendrites* extend from the cell body. The function of dendrites is to receive incoming signals sent by other neurons. In contrast to having multiple dendrites for input, neurons have a single tubular output extension called *axon*. This single axon branches out into extremities known as *presynaptic terminals* which transmit the electrical signal to the (postsynaptic) dendrites of other neurons (postsynaptic cells) using special chemicals called *neurotransmitters*. The zone where these presynaptic terminals and postsynaptic dendrites communicate with the help of neurotransmitters is called the *synapse*. An axon has the ability to carry signals over distances between *0.1mm* and *2m* (Kandel et al., 2013).

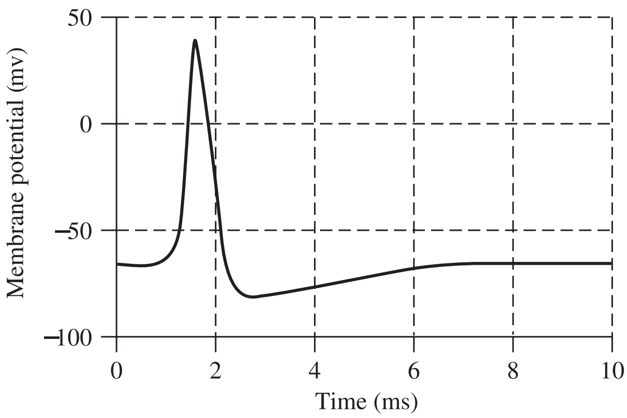


Figure 2.3: Action Potential. (Sanei and Chambers, 2008)

An action potential (AP), the electrical signal conducted through the neurons, is initiated at the initial part of the axon and propagates to the synapse. The generation of APs is an electrochemical phenomenon involving the protein structures found in the cell membrane called ion pumps and ion channels. More precisely, an AP is a temporary change in the membrane potential which normally rests at around *-70 mV*, produced by an exchange of ions through the ion channels embedded in the cell membrane. This exchange is actually caused by an incoming stimulus reaching the dendrites of the neuron. Once this temporary change reaches a threshold potential around *-55 mV*, an action potential is triggered (Figure 2.3): A sudden rise in the membrane potential (depolarization) often reaching around *+30 mV* (~*+100 mV* deflection from the resting potential) followed by a symmetrical fall (repolarization) ending below the resting potential at around *-90 mV* (hyperpolarization). The membrane returns to its resting potential after this short (a few milliseconds) hyperpolarization phase.

The brain receives, analyzes and carries information with the help of APs. An important functional characteristic of the brain is that the specificity of an information is not defined by the form of the signal but by the pathway the signal travels in the brain. It is the interpretation of signal patterns and pathways which leads to the sensation of several external stimuli (Kandel et al., 2013).

2.3 Measuring Brain Activity

A BCI requires a method for observing the brain activity produced during various cognitive paradigms. There exists several methods (Table 2.2) for sensing this activity each with its own pros and cons. We can categorize available methods in terms of the *invasiveness* and the *neurophysiological* origin of the measured activity.

Two other parameters defined below are also important to assess the applicability of the technique in the BCI field:

- *Temporal resolution* is the smallest time period of neural activity that can be reliably observed by the method.
- *Spatial resolution* is the smallest neuronal area that can be reliably accessed by the method.

2.3.1 Invasiveness

Invasiveness is a measure of how deep is a sensor going through the skin. Electroencephalography (EEG), magnetoencephalography (MEG), functional magnetic resonance imaging (fMRI) and functional near-infrared spectroscopy (fNIRS) are all *non-invasive* methods.

In contrast to non-invasive methods, *invasive* methods need to implant microelectrodes inside the skull. In electrocorticography (ECoG), microelectrodes are placed on the surface of the cortex during a surgery, while intracranial (or intracortical) recordings use arrays of microelectrodes implanted inside the cortex (Figure 2.4[3]).

Since ECoG electrodes stays on the surface of the cortex, it is sometimes referred to as a *partially-invasive* technique (Demetriades et al., 2010).

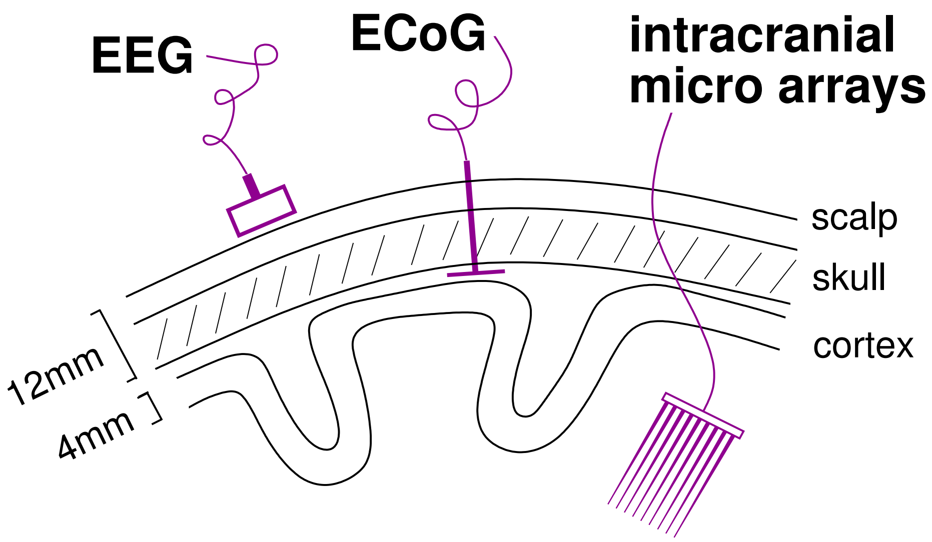


Figure 2.4: Invasiveness of EEG, ECoG and Intracranial Recordings. (Courtesy of B. Blankertz)

[3] `https://wiki.ml.tu-berlin.de/wiki/NT/Courses/SS13_IL_AAND`

2.3.2 Neurophysiological Origin

The neurophysiological origin of the measured activity can either be electrophysiological or hemodynamic (Nicolas-Alonso and Gomez-Gil, 2012).

When neurons are activated, synaptic currents are produced within the dendrites. The magnetic and electrical fields generated by these currents constitute the so-called *electrophysiological* activity. These activities can be measured invasively or non-invasively using MEG, EEG, ECoG and intracranial recordings.

The body adjusts its blood flow to deliver oxygen and glucose to active tissues during physical activities. The rapid delivery of blood to active neurons in the brain is called the *hemodynamic* response. These metabolic changes can be observed using imaging methods like fMRI and fNIRS. Since the hemodynamic response is the consequence of an augmented neuronal activity, these methods can be described as indirect methods (Nicolas-Alonso and Gomez-Gil, 2012).

2.3.3 Overview of Methods

Although each of the imaging methods mentioned before can be used in a BCI system, EEG surpasses other methods due to its high temporal resolution, portability, non-invasiveness and low cost. Consumer grade low cost EEG devices are also available making the technology more ubiquitous. The rest of this work will solely be focused on non-invasive EEG based BCI systems.

fMRI and MEG require huge devices which are very expensive, non-portable and uncomfortable. ECoG and intracranial recordings can acquire high quality signals for BCI but they are not easily applicable due to their invasive nature. Once implanted, their signal quality can gradually become weaker in long term because of tissue reaction issues.

fNIRS is recently gaining popularity for portable and non-invasive BCI design among researchers (Coyle et al., 2007; Pfurtscheller et al., 2010; Fazli et al., 2012). Although

Table 2.2: Comparison of Brain Imaging Methods (Nicolas-Alonso and Gomez-Gil, 2012)

Method	**Temporal Resolution**	**Spatial Resolution**	**Invasiveness**	**Activity**	**Portability**
EEG	~0.05s	~10mm	Non-invasive	Electrical	Portable
MEG	~0.05s	~5mm	Non-invasive	Magnetic	Non-portable
ECoG	~0.003s	~1mm	Invasive	Electrical	Portable
Intracortical	~0.003s	~0.05mm - 0.5mm	Invasive	Electrical	Portable
fMRI	~1s	~1mm	Non-invasive	Hemodynamic	Non-portable
fNIRS	~1s	~5mm	Non-invasive	Hemodynamic	Portable

it has a low temporal resolution; the ease of installation over the scalp and its simplistic electronic design will probably make it an even more popular acquisition technique in the future years.

2.4 Principles of EEG

2.4.1 Electrode Placement

Human EEG is recorded using an internationally recognized electrode naming and placement standard called 10-20 system (Jasper, 1958) (Figure 2.5). This standard is based on the relationship between electrode locations and the underlying area of the brain. A combination of a letter and a number is further used to identify each electrode location.

The letters *F, Fp, T, C, P* and *O* respectively denotes **F**rontal, **F**ronto**P**olar (or **F**rontal **P**olar), **T**emporal, **C**entral, **P**arietal and **O**ccipital lobes. (Note that the *C* letter is only meaningful as a notation to define the central line as the brain does not have an area called central lobe.) An A is used to refer to earlobes. Electrodes over the left hemisphere are suffixed with odd numbers and those over the right hemisphere are suffixed with even numbers. A *"z"* instead of a number refers to an electrode placed on the midline, which is named the *vertex*.

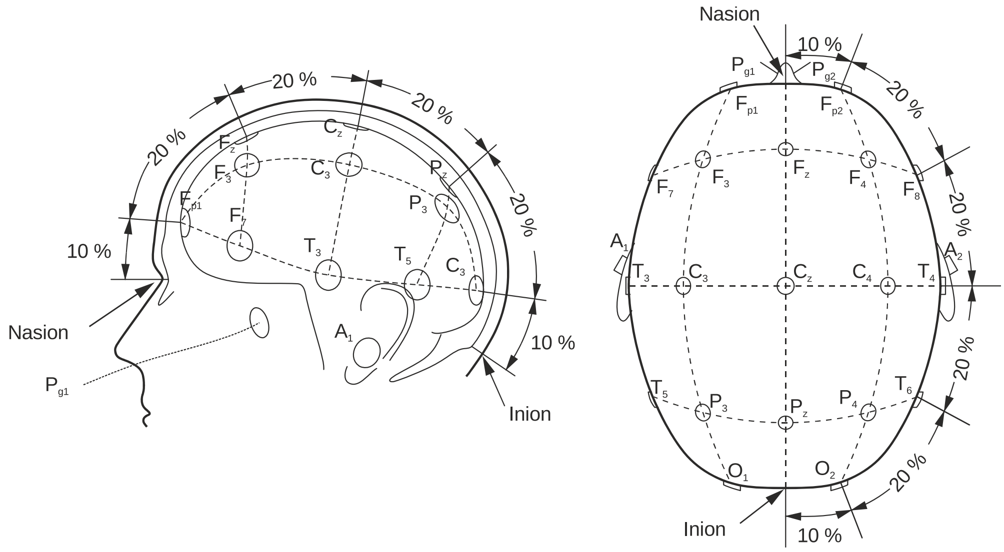


Figure 2.5: International 10-20 System. (Nicolas-Alonso and Gomez-Gil, 2012)

Two anatomical landmarks are used to define the longitudinal axis over the scalp: First, the *Nasion (Ns or Nz)*, which is the depressed area between the eyes where the bridge of the nose joins the forehead; second, the *Inion (In or Iz)*, which is indicated by a bump at the lower rear part of the skull. From these landmarks, Ns-In perimeters are divided into 10% and 20% intervals and electrode locations are fixed at those division points. Three other electrodes are placed on each hemisphere (F3,C3,P3 and F4,C4,P4) equidistantly from the already placed adjacent electrodes. The percentage of division intervals clearly reveals why the system is named after the term 10-20.

Another widely used electrode placement schema is the full 10-10 combinatorial system (1994) which is a sophisticated 10-20 variant with more and more electrodes placed in between 10-20 locations (Figure 2.6). New letters are introduced to define intermediate electrode sites: *AF* is between Fp and F, *FC* is between F and C, *FT* is between F and T, *CP* is between C and P, *TP* is between T and P, and finally *PO* is between P and O. The colored locations are actually T3, T4, T5 and T6 electrodes in 10-20 system but they are renamed to T7, T8, P7 and P8 in this modified schema.

A new 10-5 extension with 345 electrodes was also proposed by Oostenveld and Praamstra (2001) for high resolution EEG studies.

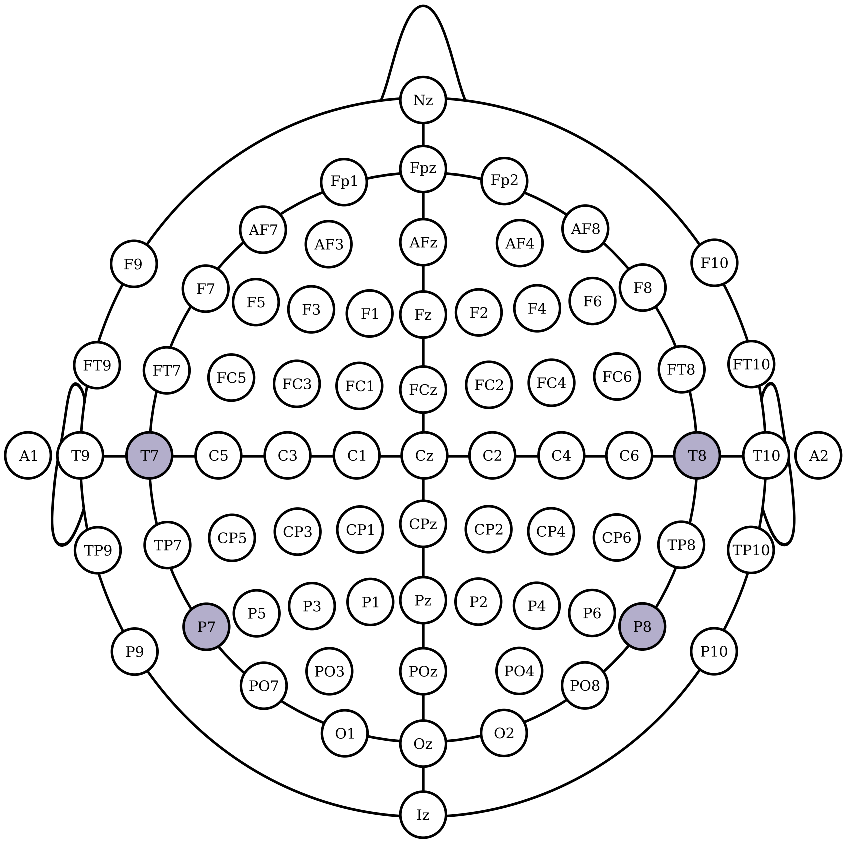
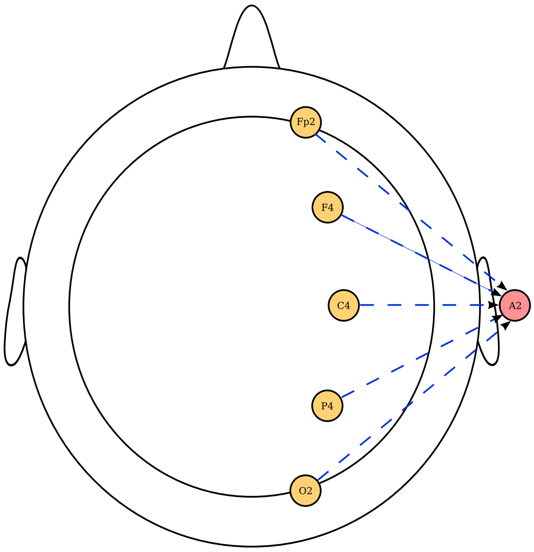


Figure 2.6: 10-10 Combinatorial System (Drawing courtesy of Marius 't Hart)

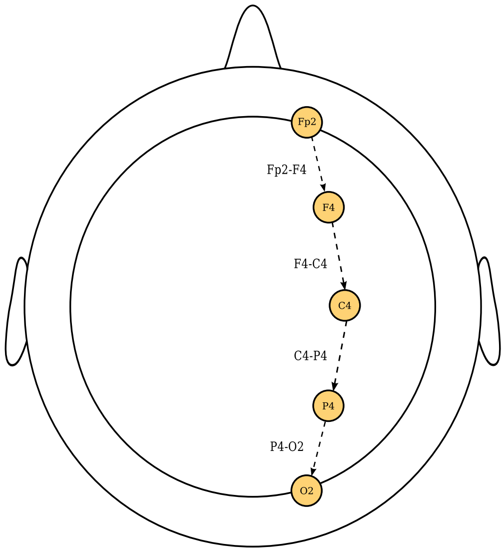
2.4.2 Montage and Recording

What is measured in EEG is defined as potential differences between pairs of electrodes placed on various scalp locations (Nunez and Srinivasan, 2006). One of the electrodes is generally called *recording* or *signal* electrode while the other is defined as the *reference* electrode. It is important to note that although the adjective *reference* seems to designate an electrode which captures an unchanging baseline/neutral signal, both electrodes actually record real and alternating brain signals (Wolpaw and Wolpaw, 2012).

Referential recording refers to a montage where EEG is recorded between each recording electrode and a reference electrode with a fixed position (Figure 2.7a). This is the montage generally used in cognitive studies and BCIs.



(a) Referential Montage



(b) Bipolar Montage

Figure 2.7: A Comparison of Referential and Bipolar Montages

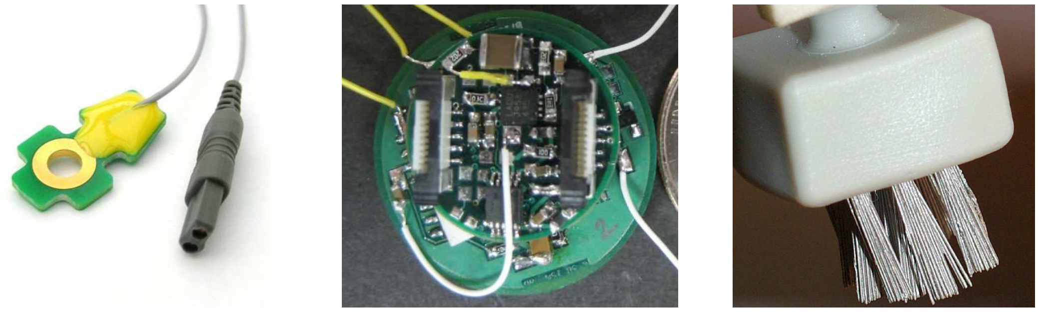
In contrast, *Bipolar recordings* measure potential differences between adjacent/very close electrodes: The reference electrode is not fixed at a specific location but varies according to the recording electrode (Figure 2.7b).

It is trivial to switch between montages with basic arithmetic operations once EEG is acquired and digitized. Re-referencing to another electrode is also possible at this stage.

2.4.3 Electrode Types

There are basically two types of electrodes used for recording EEG: *Passive* electrodes and *active* electrodes.

Passive electrodes are tiny metal disks usually made of tin, gold, silver or silver/silver-chloride (Ag/AgCl) connected to an amplifier through electrical wires. The signal they acquire is then amplified in the external amplifier circuitry. Since brain signals acquired through the scalp have amplitudes ranging between 10-100uV (Sanei and Chambers, 2008), higher amplitude noise sources like head movements, environmental factors and electrical line noise (A 50 or 60 Hz frequency signal depending on the country) have



(a) (b) (c)

Figure 2.8: Different Types of Electrode: (a) A passive electrode by *g.tec* (b) An active electrode (Sullivan et al., 2007) (c) A dry electrode prototype (Grozea et al., 2011)

the risk to garble the signals as their amplitudes become even higher after amplification. To avoid this problem as much as possible, electrode cables must be short, shielded and fixed.

A good contact between the scalp and the electrodes is also crucial to improve the signal-to-noise ratio (SNR) of the acquired signals. A layer of conductive gel paste is generally applied before recordings to reduce the skin-electrode impedance (opposition to current). Unfortunately, the application of the gel paste is cumbersome, time consuming and leaves pasty residue that will not go away without washing. An easier and cleaner alternative to gel paste is to put sponge-like pads between the electrode and the scalp and to soak them with saline solution (e.g. salt and water). This sponge-saline approach is the one preferred in Emotiv's wireless EEG headsets. The obvious disadvantage of this method is that the impedance goes up as the sponges dry (Wolpaw and Wolpaw, 2012).

On the other hand, *dry* electrodes that do not require the application of a conductive material is heavily researched to improve the ergonomics of EEG recordings (Popescu et al., 2007; Grozea et al., 2011). These electrodes generally penetrate through the hair with their fiber-like electrode tips to increase the conductivity.

Active electrodes make use of a small built-in circuitry to amplify the signals before the transmission takes place. The preamplified brain signals are thus more robust against external noise sources mentioned above since the additive noises are not preamplified.

Passive electrodes are generally the preferred type of electrode in EEG recordings since they are simple to design and cheap to manufacture (Wolpaw and Wolpaw, 2012) compared to expensive and sophisticated active electrodes. A visual comparison of the mentioned sensor technologies can be seen in Figure 2.8.

2.4.4 Brain Rhythms in EEG

The frequency (or spectral) content of EEG signals is generally divided into five frequency bands: Delta rhythm (0.1-3.5 Hz), theta rhythm (4-7.5 Hz), alpha rhythm (8-13 Hz), beta rhythm (14-30 Hz) and gamma rhythm (> 30 Hz) (Niedermeyer and da Silva, 2005). A sixth one called mu rhythm (8-12 Hz) can be observed when motor neurons are in the idling state (Wang et al., 2010). Although the frequency intervals of mu and alpha rhythms seem to overlap, alpha rhythm is observed over the visual cortex while the mu rhythm is prominent over the sensorimotor cortex.

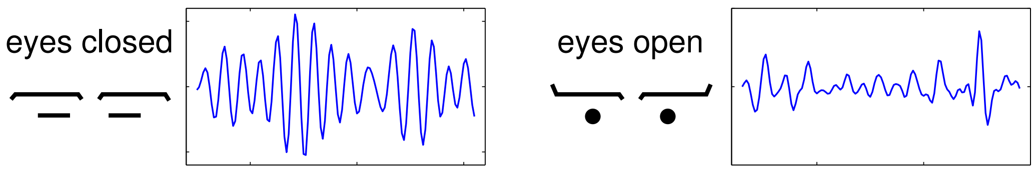


Figure 2.9: Alpha Rhythm Over Oz (Courtesy of B.Blankertz)

The observation or absence of these rhythmic activities is generally associated with external stimuli processing, sleep states, cognitive actions or pathological findings. For example, an alpha rhythm around 10 Hz over the visual cortex is attenuated during visual processing, e.g. while the eyes are open (Figure 2.9[4]).

2.5 BCI Paradigms

There are several paradigms used in BCI design for extracting control information out of the brain. A BCI paradigm is defined as active/endogenous or reactive/exogenous based

[4]https://wiki.ml.tu-berlin.de/wiki/NT/Courses/SS13_IL_AAND

on the underlying cognitive mechanism of the paradigm used.

2.5.1 Event-Related Potentials

Event-Related potentials (ERP) are defined as potential changes in neural activity associated with specific cognitive events (Luck, 2005).

P300 is a widely used and researched ERP in BCI field. It is a positive (a positive amplitude change happens in the ongoing activity) exogenous response elicited by the brain approximately 300ms after the presentation of an infrequent target stimulus in a set of frequent non-target stimuli (Polich, 2007). A special letter matrix (Figure 2.10) was proposed by Farwell and Donchin (1988) in order to use this neurophysiological fact in the BCI field. The system randomly highlights the rows and the columns of the letter matrix while the user focuses on the letter that he/she wants to select. Each letter is highlighted once for its row and once for its column in a sequence of $2N$ highlights for a NxN square letter matrix. The P300 response evoked by these infrequent highlights are further detected to select the focused letter.

A	G	M	S	Y	*
B	H	N	T	Z	*
C	I	O	U	*	TALK
D	J	P	V	FLN	SPAC
E	K	Q	W	*	BKSP
F	L	R	X	SPL	QUIT

Figure 2.10: Layout of the Farwell-Donchin P300 Speller

P300 response is also evoked in auditory and tactile stimulation.

2.5.2 Steady-State Visual Evoked Potentials

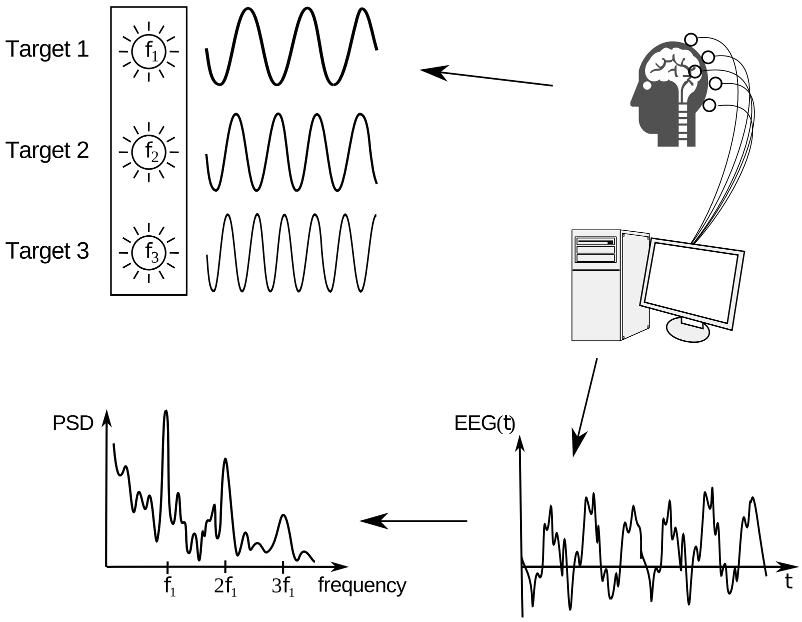


Figure 2.11: Diagram of a SSVEP BCI (Chumerin et al., 2012)

A steady-state visual evoked potential (SSVEP) is an exogenous response to a repetitive visual stimuli which usually oscillates at the fundamental and harmonic frequencies of the flickering stimulus (Wu et al., 2008).

In a typical SSVEP BCI setup, targets are generally represented to the user in a flickering fashion be it an LED light, a pattern on a CRT or LCD screen, etc (Figure 2.11). The type of stimulation device, the color and the shape of the stimulus, the frequency band of the oscillation rate and the phase between stimuli are characteristics of the light stimuli which can affect the SSVEP (Zhu et al., 2010).

Since SSVEP is a response to a repetitive visual stimulus, it is prominent and observable through the occipital locations near the primary visual cortex (Herrmann, 2001).

2.5.3 Slow Cortical Potentials

Slow Cortical Potentials (SCP) are voltage changes in EEG which occur slowly over time, e.g. between 0.5-10 seconds (Wolpaw and Boulay, 2010). The fact that these slow potentials can be consciously regulated by healthy and paralyzed people, makes SCP a choice for BCI design (Birbaumer et al., 2000; Hinterberger et al., 2004; Birbaumer, 2006).

SCP-based BCIs are active/endogenous systems as the user has to voluntarily adjust the polarity (negative/positive) of their slow potentials according to some neurofeedback protocol (Jackson and Mappus, 2010). They can be used to select between binary targets (target selection) since the control signal is a bi-state negative/positive shift in slow potentials. This binary selection can also be extended to a speller application in which a letter is recursively selected by halving the alphabet in each step (Birbaumer et al., 2000).

2.5.4 Sensorimotor Rhythms

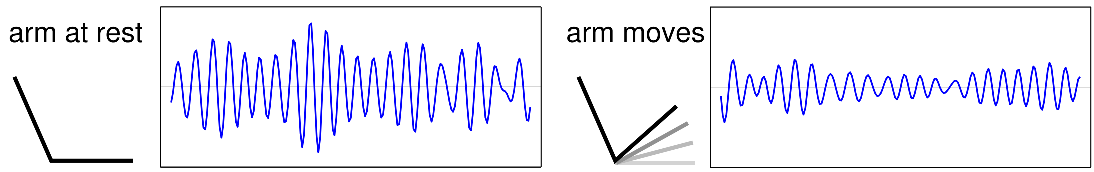


Figure 2.12: Mu Rhythm Over Sensorimotor Cortex (Courtesy of B.Blankertz)

Sensorimotor rhythms (SMR) are idling (rhythms observable while the user is at rest) mu and beta rhythms prominent over the sensorimotor cortex which are desynchronized (suppressed) with the activation of the motor system like the movement of hands or foot (Sellers et al., 2010). These changes not only happen with the actual movement but also with the imagination of movement, e.g. motor imagery (MI) (McFarland et al., 2006). The terms SMR, MI or mu rhythm can be used interchangeably to define this type of BCI.

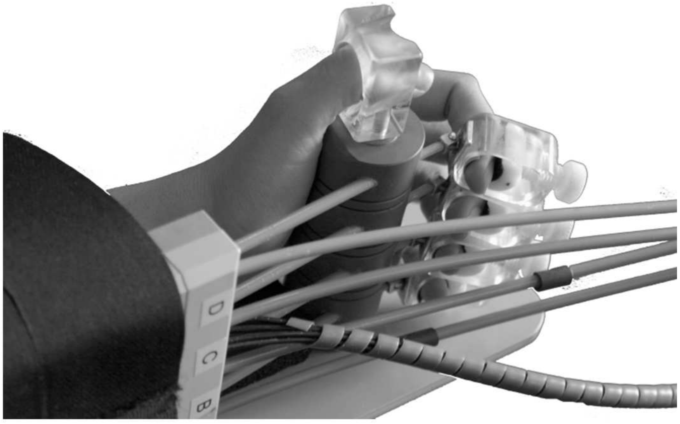


Figure 2.13: Hand Orthosis for Neurorehabilitation (Ramos-Murguialday et al., 2012)

SMR-based BCIs are active/endogenous systems as the user has to initiate/plan/imagine a movement to adjust their EEG rhythms. SMR-based BCIs are used in cursor control applications to select between targets (Wolpaw et al., 1991; Wolpaw et al., 2003; Vaughan et al., 2006), neurorehabilitation (Figure 2.13) applications (Prasad et al., 2009; Ramos-Murguialday et al., 2012; Ortner et al., 2013), orthotics and prosthetics control (Guger et al., 1999; Pfurtscheller and Neuper, 2001).

3 MATERIALS AND METHODS

3.1 Materials

There exists three important hardware components of our embedded BCI design: an embedded computer to manage all kinds of interaction between the individual parts of the BCI, an EEG headset for brain signal acquisition and finally an external actuator to reflect the choices of the BCI user to the environment, e.g. the arms of a humanoid robot for this study.

3.1.1 BeagleBone Black

BeagleBone Black (BBB) is a 45$ single board computer released in 2013. It has 1GHz TI AM3359 Sitara ARM Cortex-A8 microprocessor, 512MB DDR3 memory, 3D accelerated PowerVR SGX530 graphical processing unit (GPU) with HDMI output, onboard 2GB embedded MMC (eMMC) flash storage pre-loaded with Ångström Linux distribution (Figure 3.1). Along with a single USB 2.0 host port and 10/100 RJ45 Ethernet port for general purpose connectivity, the board also provides a wide variety of low-level expansion interfaces: 66xGPIO, 5xUART, 8xPWM, 8xADC, 2xI^2C, SPI and CAN. A 4 port bus powered external USB hub is used for increasing the number of USB devices that can be connected to the BBB.

We first installed Ubuntu to an 8GB micro SD card as it is a widely adopted Linux distribution with a rich software repository. A rich software repository is important for avoiding manual compilation/installation of several tools and libraries, which in turn decreases the time needed to start experimenting with the BCI system. We also disabled several unused system services to avoid wasting processor and memory resources.

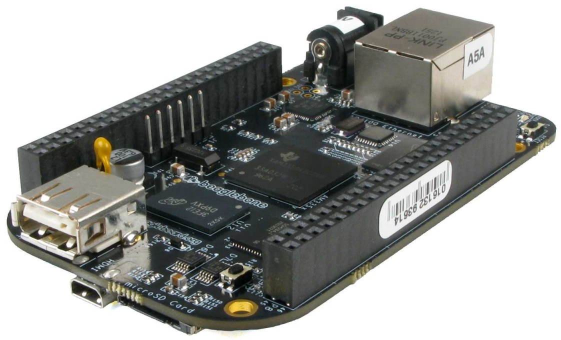


Figure 3.1: BeagleBone Black Single-board Computer

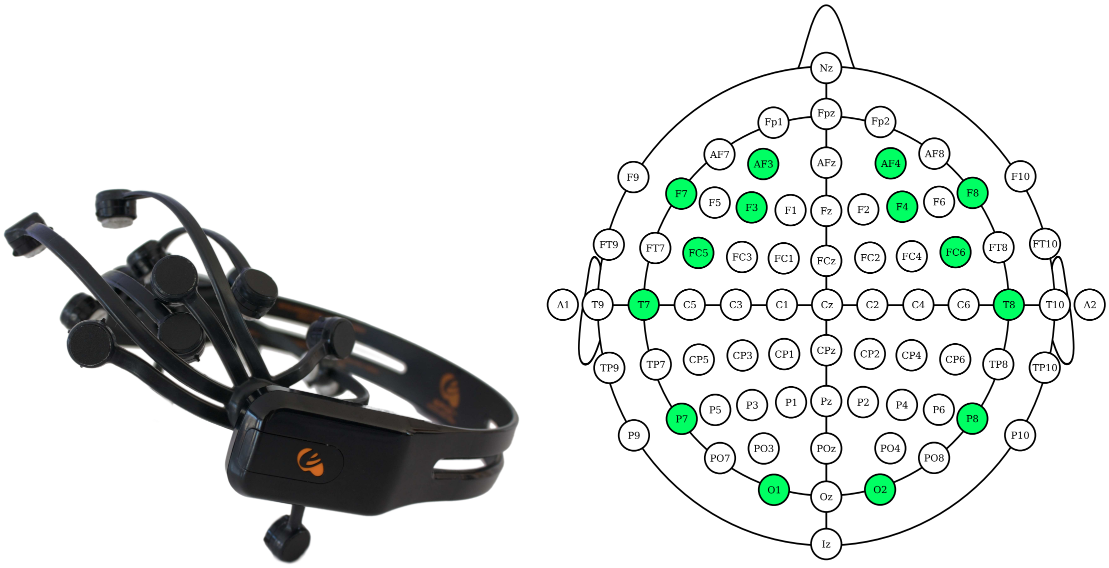
3.1.1.1 Programmable Realtime Unit

Although the Cortex-A8 processor is powerful, real-time control of high-speed external hardware and high precision tasks can be affected by OS latencies. BBB improves the situation by providing two programmable realtime units (PRU) optimized to perform embedded tasks with hard realtime constraints. The PRUs have:

- Two 32-bit RISC cores running at 200MHz (Each instruction completes in 5ns)
- 8KB data memory and 8KB instruction memory
- 12KB shared memory
- A small instruction set

It is sometimes possible to encounter delays in OS scheduling while EEG acquisition, external stimulation (like SSVEP stimulation for example) are both running simultaneously. This can negatively impact the precision of flickering intervals causing the BCI to perform badly. Offloading stimulation or any other high precision tasks to the PRU can resolve jitters and delays as PRU is a distinct microcontroller unit which is completely decoupled from the main CPU of the device.

By now, the PRU can only be programmed using assembly language. A helper library for C and Python is available to launch and terminate custom programs written for the PRU. It is also possible to share data between the PRU and the CPU using shared memory.



(a) Emotiv EEG Headset (b) Electrode Locations

Figure 3.2: Emotiv EEG Headset and Electrode Locations

3.1.2 Emotiv EEG

Emotiv EEG (Figure 3.2a) is a battery-powered, wireless consumer headset which can acquire 14 channels (Figure 3.2b) of EEG signal. Although Emotiv EEG is primarily researched for gaming and entertainment applications (van Vliet et al., 2012; Chumerin et al., 2013), several research activities are targeting it to assess and exploit its usability for assistive BCI applications (Liu et al., 2012; Badcock et al., 2013; Caglayan and Arslan, 2013; Guneysu and Akin, 2013; Choi and Jo, 2013).

The headset internally applies a notch filter (At line frequency 50/60Hz) and a 5^{th} order band-pass filter (0.2-45Hz) to the signal. Although the internal sampling rate of the headset is 2048Hz, the device downsamples the signal to 128Hz before sending them to the computer. Full technical specifications found in the manufacturer's website[5] are summarized in Table 3.1.

[5] http://www.emotiv.com/eeg/download_specs.php

Table 3.1: Technical Specifications of Emotiv EEG Headset

Number of channels	14 (+ CMS/DRL references, P3/P4 locations)
Channel names	AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4
Sampling method	Sequential sampling, single ADC
Sampling rate	128 SPS (2048 Hz Internal)
Resolution	14 bits 1 LSB = 0.51uV
Bandwidth	0.2-45Hz, digital notch filters at 50Hz and 60Hz
Filtering	Built-in digital 5th order Sinc filter
Dynamic range (input referred)	8400uV (pp)
Coupling mode	AC coupled
Connectivity	Proprietary wireless, 2.4GHz band
Battery life	12 hours (typical)
Impedance measurement	Real-time contact quality using patented system

Emotiv EEG uses a fixed reference electrode pair around P3/P4 region as the default reference location. The manufacturer also provided an alternative reference electrode pair right behind the ears. It is possible to switch to that reference location by removing the plastic rubber pads and inserting the spongy pads to those spots instead of the default reference locations[6].

3.1.2.1 Official Software Development Kit (SDK)

Emotiv provides an SDK for Windows, Mac OS X and Linux operating systems but the provided SDK is closed-source and only available for x86 CPU architecture. This means that it is not possible to use the SDK on ARM embedded computers like Raspberry Pi or Beaglebone Black. Although Emotiv recently made available some closed-source C/C++ libraries initially built for N900 ARM smartphones (Stopczynski et al., 2011), they are still far from being usable due to possible binary incompatibility between different ARM

[6] http://emotiv.com/ideas/forum/forum12/topic2507

architectures and the lack of documentation. As of now, the only reliable way of using the Emotiv headset with an ARM based embedded computer is to use the open-source protocol reverse-engineered by Cody Brocious and Kyle Machulis.

3.1.2.2 Open-Source Protocol

According to the protocol details[7] the USB dongle acts as a simple Human Interface Device (HID) which relays an AES encrypted data packet of size 32 bytes with a rate of 128 packets/sec. Each decrypted EEG packet is tagged with an 8-bit sequence number ranging from 0 to 127. A sequence number greater than 127 carries the battery level of the device instead of EEG data. Real-time contact quality information for each sensor is also embedded within the EEG packets in an interleaved order: 0^{th} packet contains the contact quality for F3, 1^{st} packet for FC5, and so on.

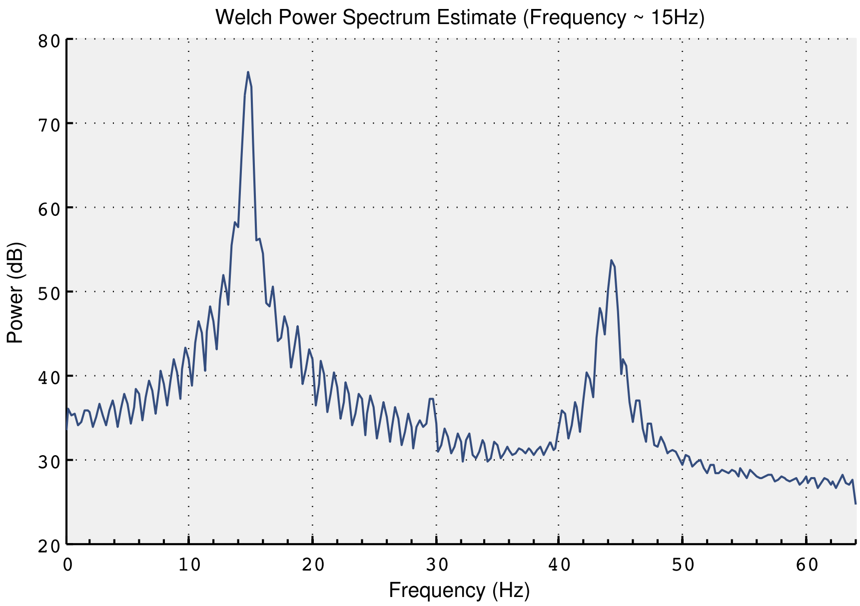


Figure 3.3: Validation of the Open-Source Protocol

In order to validate the open-source protocol, we connected a function generator to the headset. The generator is adjusted to produce a $15Hz$ sinusoidal waveform which is injected to the O2 electrode of the headset.

[7]`https://raw.github.com/openyou/emokit/master/doc/emotiv_protocol.asciidoc`

The frequency spectrum of the signal acquired over O2 clearly shows the fundamental and harmonic frequencies of the injected waveform (Figure 3.3). This proves that the protocol correctly decrypts and resolves the data packets streamed by the headset.

3.1.2.3 Python-emotiv

Since we decided to realize the whole BCI in pure Python, we developed an object oriented Python module called *python-emotiv*[8] implementing the open-source protocol to access the device on Linux. The module uses *libusb* to access the dongle in a cross-platform manner although it has only been tested on Linux so far.

As of December 2013, the features of *python-emotiv* can be summarized as follows:

- Support for Emotiv EEG using libusb on any platform with Python installed
- Support for reading 14 channel raw EEG, 2-axis gyro, contact qualities and battery status
- Synchronous acquisition of the data per single sample or requested duration
- Ability to save the acquired data as *FieldTrip* (Oostenveld et al., 2011) compatible Matlab (.mat) data
- Ability to stream EEG data through *Lab Streaming Layer*[9]

python-emotiv was received well by the open-source community. An individual developer forked the project and added Mac OS X support[10] to it. It is also used in a newly started BCI controlled wheelchair project[11].

3.1.3 Kondo KHR-3HV Humanoid Robot

Kondo KHR-3HV is a 17 degrees of freedom humanoid robot manufactured by *Kondo Kagaku* (Figure 3.4). The RCB-4 microcontroller of the robot has the ability to drive up to 35 serial servos. The board is also equipped with several I/O ports to extend the robot with sensors and other add-ons.

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[8] `https://github.com/ozancaglayan/python-emotiv`
[9] `https://code.google.com/p/labstreaminglayer`
[10] `https://github.com/simlay/python-emotiv`
[11] `http://braingizer.blogspot.com`

Figure 3.4: Kondo KHR-3HV Humanoid Robot

The motions for KHR-3HV is designed and programmed into the microcontroller using a Windows application called *Heart-to-Heart*. All communication between the computer and the robot (both for programming and controlling) is realized over a serial USB dongle. Once the motions are designed and written into the microcontroller using the proprietary software, it is possible to play those preprogrammed motions and control individual servos separately with the open-source and community contributed *libkondo4* library[12]. The library has also language bindings to allow controlling the robot using Python and Java.

3.2 Methods

The interaction of the materials described in the previous section is realized through the intercommunication of various software blocks written in Python. These software blocks are explained in detail in the following section.

[12]`https://bitbucket.org/vo/libkondo4`

3.2.1 SSVEP Stimulation

3.2.1.1 Hardware Design

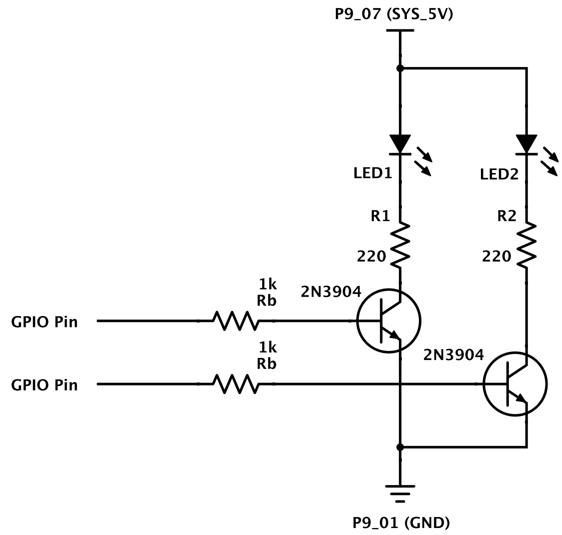

Figure 3.5: Schematic of SSVEP LED Stimulator

BBB has several General-Purpose Input/Output (GPIO) pins that can be used to communicate with external devices and circuits. These pins can be raised HIGH (+3.3v) or LOW (0v) using Adafruit BBIO library for Python.

In order to preserve the portability of the system, we decided to use BBB's Input/Output capabilities for LED SSVEP stimulation. A simple digital circuit is designed to drive LED light sources using transistors (Figure 3.5). We had to use transistors to switch the LEDs because BBB can not provide enough current through its GPIO pins to light LEDs brightly. The transistors rapidly switch the current going to the light sources which can be powered by an external power source.

The final montage of the stimulator using 2 red 5x7 LED matrices can be seen in Figure 3.6. Note that only 9 LEDs per LED matrix are enabled as using all of them is not comfortable for visual perception.

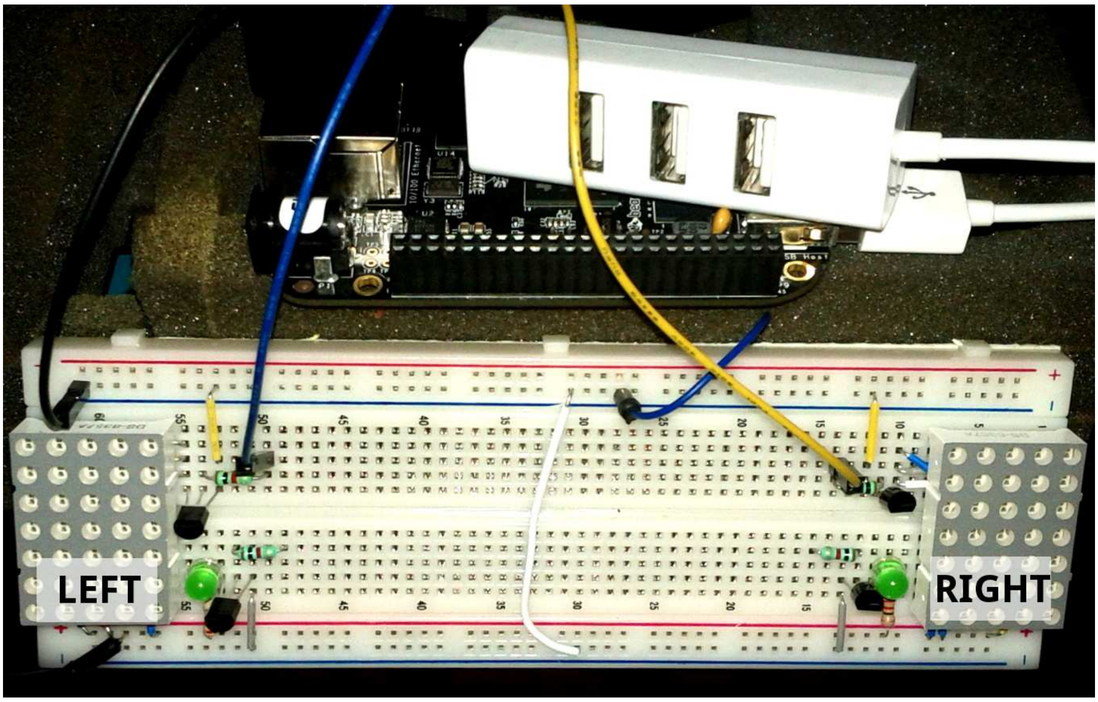

Figure 3.6: LED Matrix Montage on BeagleBone Black

3.2.1.2 SSVEP Software Block

A Python script (`bbb-bci-ssvepd.py`) is written to manage the external stimulation circuit. To start the stimulator, the flickering frequencies, f_1 and f_2 are passed as command line arguments to the script which changes the mode for GPIO pins to *output*, computes the triggering periods T_1 and T_2 for each frequency according to the formula $T_i = \frac{1}{2f_i}$ and finally blocks until a signal (namely `SIGUSR1` signal) is sent to it to start the stimulation. Once the process receives this signal, it continuously compares the system time and previously computed triggering periods to decide whether it is time for changing the state of the lights or not. The stimulation continues until the arrival of the same signal.

The correctness of the flickering frequencies is tested using an Arduino and a simple software written with the *FreqMeasure*[13] Arduino library. It has been observed that the flickering frequencies are pretty accurate during a BCI experiment which led us to the decision that using the PRU for stimulation is not necessary for the proposed design.

[13] `http://www.pjrc.com/teensy/td_libs_FreqMeasure.html`

The stimulation frequencies are currently tuned to $f_1 = 17Hz$ and $f_2 = 19Hz$ to represent respectively the left and the right arm of the robot.

3.2.2 Signal Processing and Classification

The signal processing and classification (SPC) block is implemented as a Python function which runs as a separate process in the background. The main block and the SPC are connected to each other using a UNIX inter-process communication (IPC) method called *pipe*. SPC continuously receives and analyzes EEG data and sends back a classification result to the main block over this established pipe channel.

Once a new EEG chunk is received by the SPC block, the predetermined channel of interest is:

- Detrended to remove the linear trend,
- High-pass filtered using 2nd order Butterworth filter with a cutoff frequency of $5Hz$ to eliminate low frequency noise components.

The power spectral density (PSD) of the received chunk is estimated using autoregressive (AR) Burg's method (Kay and Marple, 1981) with model order set to 64 (Burg's method is available in Python through the *spectrum*[14] package).

A cumulative moving average of the PSD estimates of previously received chunks and the new one is then calculated for smoothing the spectrum and thus improving the SNR. A weighted sum of the PSD estimates at the 1st harmonic and at the neighborhood of the 2nd harmonic is used as a score for each flickering frequency f_i:

$$Score(f_i) = PSD(f_i) + \frac{PSD(2f_i - 1) + PSD(2f_i) + PSD(2f_i + 1)}{2}$$

[14]`https://pypi.python.org/pypi/spectrum`

If one of the scores win over the other one 3 times consecutively, SPC block sends it back as the classification result and waits for new data.

3.2.3 EEG Acquisition and BCI Workflow

The main acquisition block (ACQ) is actually what manages the SSVEP and the SPC block. It can actually be considered as the entry point to the BCI application.

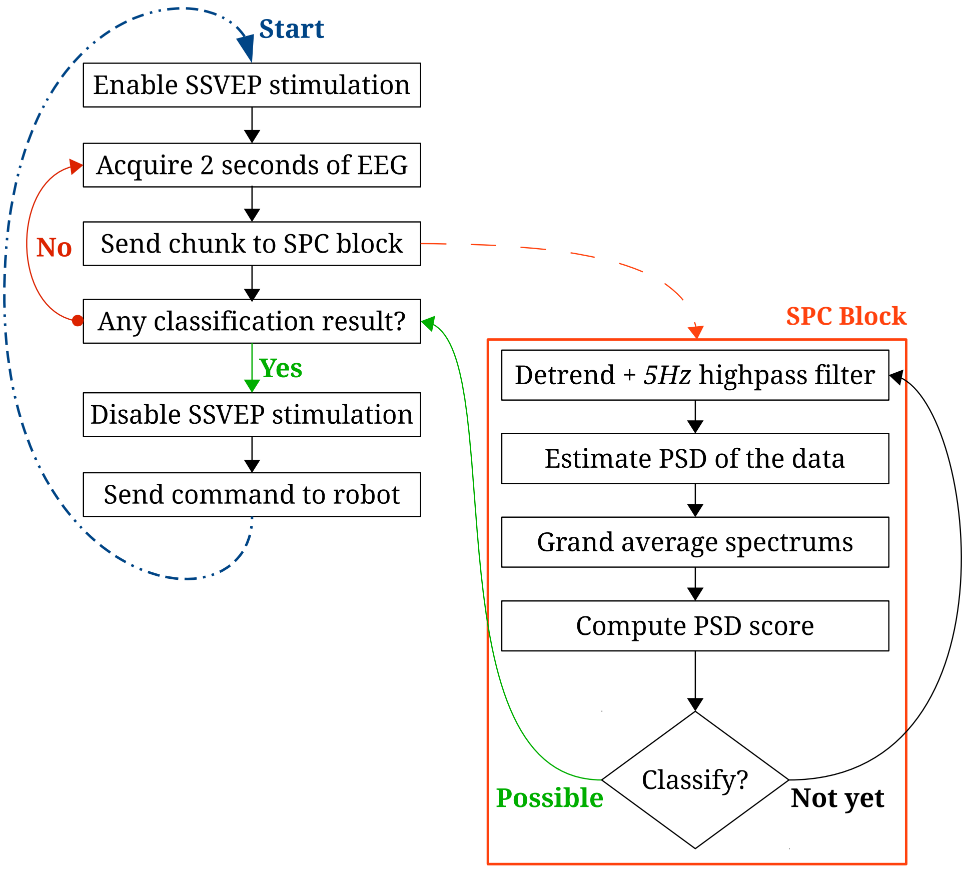

Figure 3.7: Workflow of the Proposed BCI

ACQ first launches the SSVEP block with the desired flickering frequencies. After initializing Emotiv EEG headset and establishing connection to the robot, it signals the SSVEP block to start the stimulation. ACQ continuously acquires 2 seconds length EEG chunks and sends them to the SPC block (over the pipe) until SPC sends back a classification result. Once the result is received, ACQ signals the SSVEP block to stop the stimulation and sends a control command to the robot according to the result.

The proposed BCI (Figure 3.7) can run infinitely until the user or someone else interrupts it. The length of each trial is not fixed to a predetermined value which qualifies the BCI as being a *dynamic stopping* one.

3.3 Results and Discussion

The BCI is initially tested on 2 subjects with 2 different recording sessions. Each session consisted of 6 trials of 14 seconds. 7 chunks of 2 seconds length EEG data has been used in order to classify the attended frequency. The plots of averaged PSD estimation for a subject with short hair (OC) and a subject with long hair (PU) are respectively presented in Figure 3.8 and 3.9.

A classification rate of $\%100$ has been achieved in both sessions for the subject OC while $\%66.7$ and $\%83.3$ were reached by the subject PU.

The misclassification can be caused by several reasons including movement related artifacts or poor conductivity (especially for the subject PU with long hair). Artifact rejection methods can be dynamically applied to the data during the acquisition to eliminate noisy trials or chunks of EEG.

It can also be observed empirically that the PSD estimate at the 1^{st} harmonic is more significant compared to the neighborhood of the 2^{nd} harmonic. So a scoring method solely based around the 1^{st} harmonic may improve the classification rate.

Finally, the relationship between the duration of a single EEG chunk (which is currently set to 2 seconds) and the SNR of the smoothed spectrum can be analyzed to see whether increasing the duration improves the SNR or not.

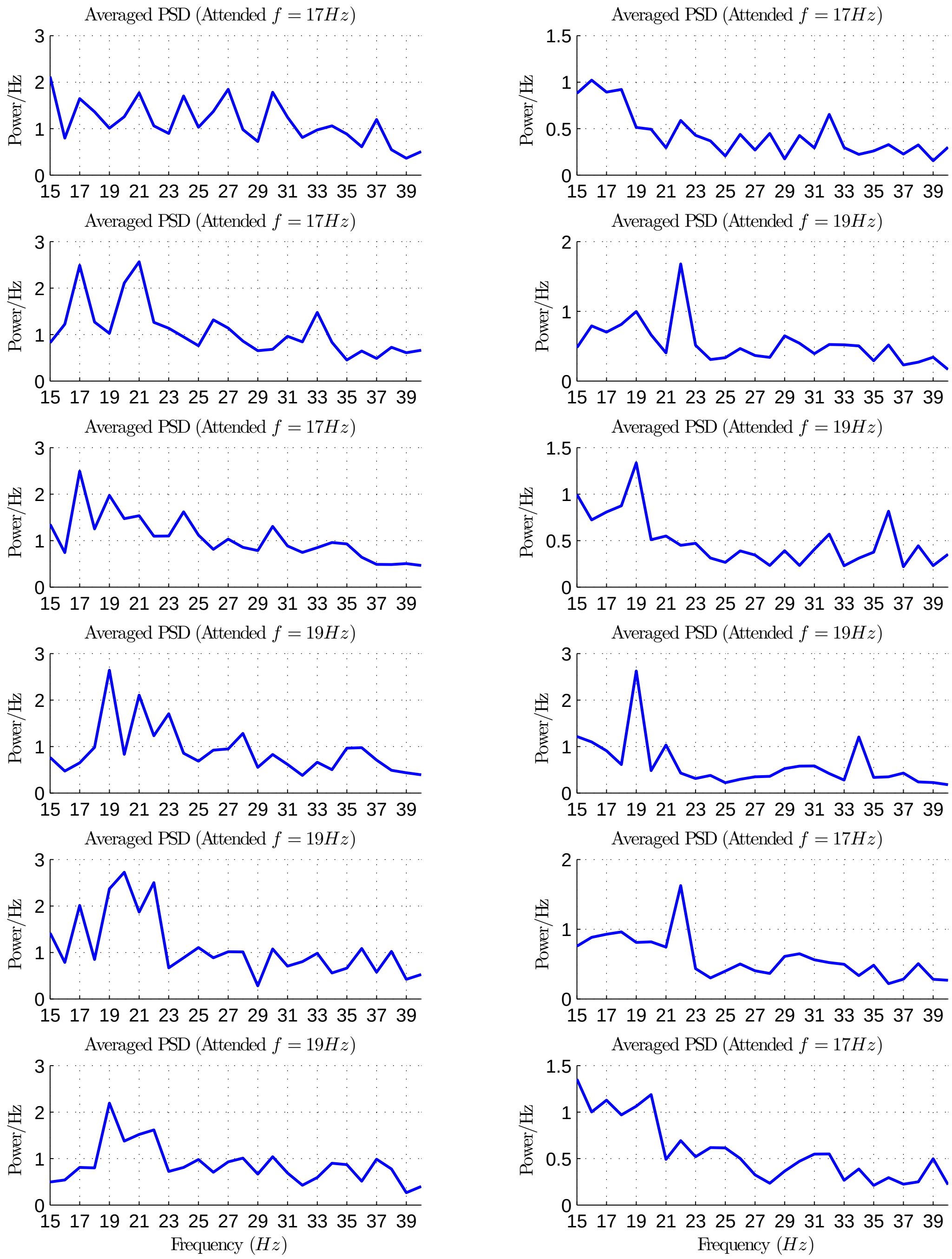

Figure 3.8: Averaged PSD Estimation of Subject OC

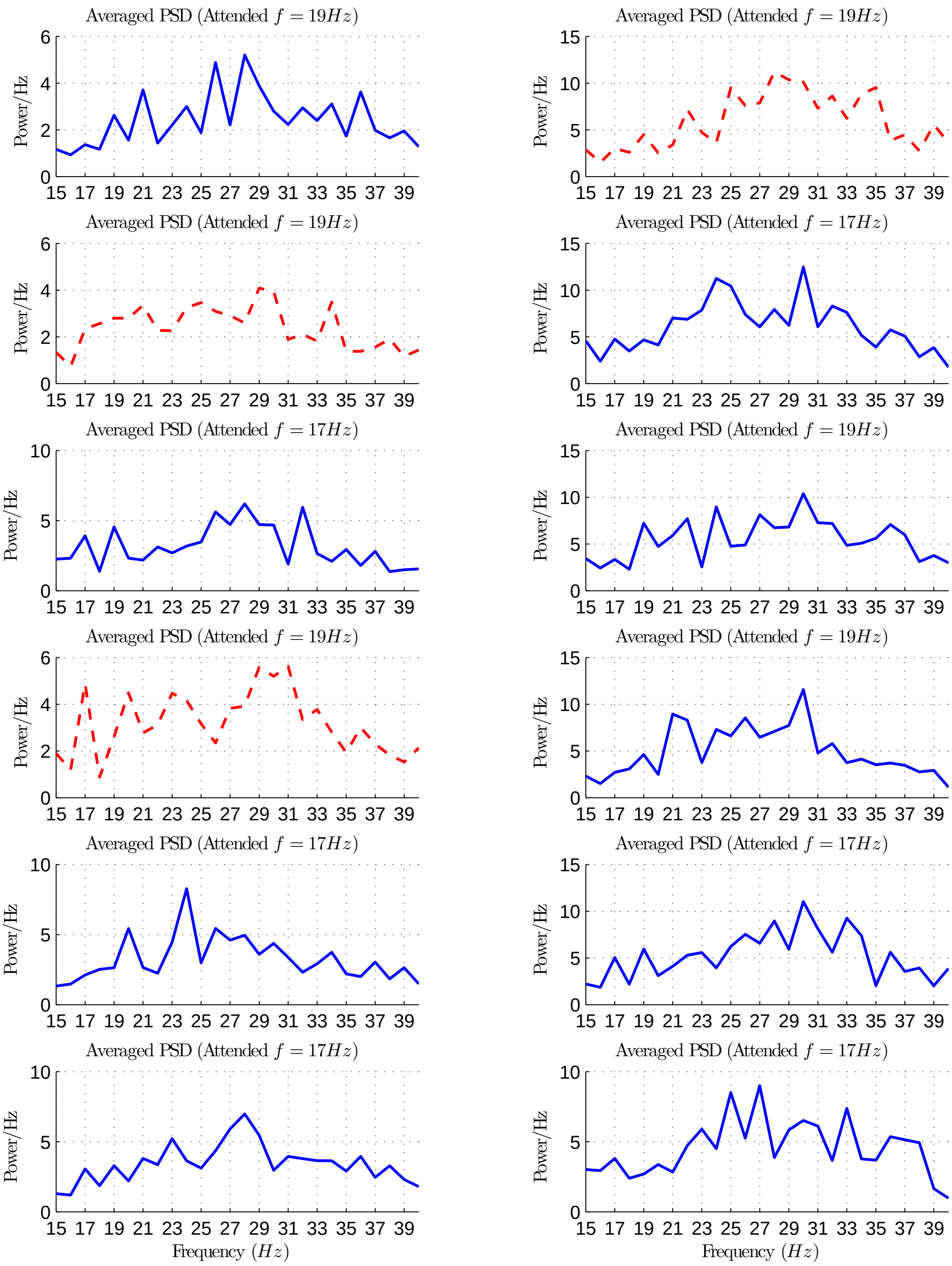

Figure 3.9: Averaged PSD estimation of subject PU. Misclassified trials are drawn with dashed lines

4 CONCLUSION

In this study, a proof of concept, portable, embedded and affordable SSVEP BCI system allowing humanoid robot control is proposed.

Initially, a free, open-source and architecture independent Python library allowing hardware access to Emotiv EEG is developed from scratch due to the lack of proper SDK support for ARM architecture. The next step was to tune and customize the selected embedded computer, namely the BeagleBone Black, to suit the needs of a complete BCI system.

All of the software blocks regarding stimuli presentation, EEG acquisition, signal processing and robot control are also implemented in Python. We thus conclude that Python is a very powerful, free and open-source programming language for a wide range of scientific research topics.

Preliminary results show that the deployment of embedded computers in the BCI field can be considered feasible depending on the selected BCI paradigm and the complexity of the overall design. To our knowledge, this is the first BCI system which completely runs on an embedded computer.

Future studies

More advanced methods like common spatial pattern (CSP) can be implemented and applied to the channels to select the most feature rich channel combination in terms of SSVEP response. Moreover, a simple training session can be applied to dynamically tune several parameters like the channel(s) of interest, trial duration and SSVEP frequencies to minimize intersubject variations. There is still enough room in BeagleBone Black to implement a machine learning based BCI using the open-source libraries like *scikit-learn* for example.

The output of the proposed BCI system can be improved and a more intelligent robotic control using ambient sensing and motion planning algorithms should be possible. It is also possible to completely change the output modality and use the BCI for answering simple yes/no questions. We have already been able to successfully integrate *espeak* speech synthesizer into our BCI to test this modality.

Finally, the whole BCI stack can be modified to run in an autonomous way once the embedded computer is turned on. For example, contact qualities of electrodes can be automatically assessed to start the BCI when the headset is placed over the scalp or the power button of the BeagleBone Black can be used to switch BCI output modality. These will turn the embedded computer into an application specific processor similar to application spefic integrated circuits (ASIC) found in many self-contained appliances.

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Biographical Sketch

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Publications

- O. Caglayan and R. B. Arslan, "Humanoid Robot Control With SSVEP On Embedded System" in Proceedings of the Fifth International Brain Computer Interface Meeting 2013, California.
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- O. Caglayan and R. B. Arslan, "Robotic Arm Control Using Brain Computer Interface" in 16th National Biomedical Engineering Meeting (BİYOMUT 2012), Turkey.
- O. Caglayan and R. B. Arslan, "P300 Based Auditory Visual Brain Computer Interface" in 20th IEEE Signal Processing And Communications Applications Conference (SIU 2012), Turkey.