ASSESSING SELF-SIMILARITY AND CROSS-SIMILARITY BETWEEN EEG PATTERNS FOR BIOMETRICAL APPLICATIONS

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ASSESSING SELF-SIMILARITY AND CROSS-SIMILARITY BETWEEN EEG PATTERNS FOR BIOMETRICAL APPLICATIONS

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ABSTRACT

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In the modern world, authentication and access control mechanisms have become a part of our daily lives. Although traditional methods are widely used, this report addresses the necessity of a more robust approach for biometric application in the access control technology. Biometrics is the science of measuring and analyzing certain unique, physiological and behavioral human characteristics, called biometric identifiers, for authentication purposes. Specifically, this research investigates the advantage of using the Electroencephalogram (EEG) as a biometric identifier; as EEG may potentially improve robustness and security, of biometric systems. EEG results from the electrical activity due to ionic current flows within the neurons of a functioning brain.

The power spectral density estimates of EEG over the combined Alpha-Beta rhythm were used as the potential discriminant feature for biometric authentication of different subjects, each performing two different activities. To classify subjects, their recorded EEG were processed and analyzed through techniques, such as power spectral density (PSD) estimation and Euclidean distance classification. Although our approach successfully classified one subject for both predesigned mental tasks accurately, it has failed to show the sufficient accuracy for the other subject.

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Chapter 1

Introduction

1.1 What is Biometrics?

The word *biometrics* finds its etymology in two ancient Greek words, *bios* (life) and *metron* (to measure); however, biometric systems as we understand them in this context are not used to "measure life," but rather the identity of a human individual by his or her unique physiological and behavioral characteristics. For security reasons, people commonly require the use of biometrics technology. While having a conversation with someone, we feel it important to know with whom we are interacting, and we want the same capability in our modern security systems, user identification. For these purposes of user authentication and access control, scientists have developed a significant number of biometric methods which are used successfully worldwide. A biometric protocol could be used either as an identification system or a verification system.

An identification system can be used to match a person's biometrics against a database to find out his or her identity by searching the closest match. It is commonly referred to as 1:N matching. Criminal watchlist application scenarios are a good example of these types of systems.

Suppose a person claims to be "X." A verification system will match and compare that person's biometric identifiers with the stored biometrics of "X." If those match, then we can say that the user is *verified*, or that he or she in indeed "X." This is referred as 1:1 matching. An access control application scenario is an example of a verification system.

1.2 What is EEG?

EEG is the measurement of the electrical potential difference between an electrode and a reference electrode of the human brain as it responds to specific stimuli. EEG is recorded in a graphical manner over time. Electroencephalography has been utilized as a unique and valuable method of recording a brain's electrical signals. It can be performed in two different ways (Benbadis et. al. 2008), either as Invasive EEG or Non-invasive EEG.

Invasive/Intracranial EEG is recorded directly from the brain through a surgically implanted electrode placed at particular regions of human brain. Non-Invasive/ Extracranial EEG is recorded from the surface or cortical layer of the human brain (Benbadis et. al. 2008).

1.3 Motivation

Biometrics, as the measurement of a person's physical features, actions, or behavioral characteristics that are distinguished between individuals, has a long history. Technological developments and intensive research have netted innovative concepts, features, and data processing approaches, and systems automation and implementation have drastically improved security systems. Additionally, new research is developing multimodal biometric systems, which simultaneously analyze more than one biometric feature in order to increase accuracy and security. Biometric systems play a crucial role in current personal identification systems, which identify one individual from among a group and verification systems, which confirm or deny an identity claim by one individual. a database. Based on the specific biometric traits used to extract desired features in a system, biometric identifiers fall into two main classes: physiological traits and behavioral traits. Existing biometric systems analyze humans' physical characteristics and extract features for pattern recognition, such as facial patterns, fingerprints, irises, hand shape, and DNA patterns, to name a few, but these standard identifiers have certain limitations. Subsequently, researchers are working to identify new types of substitute biometic traits; an EEG-based biometric is one interesting possibility.

As a person performs any activity or task, his or her brain generates different types of waves: magnetic, electrical, and metabolic signals. These brain signals can be observed, monitored, and recorded via various methods, both invasive and non-invasive. Invasive methods, in which devices are permanently implanted in the brain, are not feasible in certain applications because of the risk factor, expense, and complexity of implantation. Non-invasive methods, where brain signals are monitored and recorded by placing electrodes on the scalp of the user, are often much more feasible and practicable. These methods include positron emission tomography (PET), magnetoencephalography (MEG), optical imaging, functional magnetic resonance imaging (fMRI), and electroencephalography (EEG), one of the most widely used methods to record electrical signals within the brain. Many studies provide evidence of the uniqueness of individual EEG patterns. Biometry through EEG signals offers several benefits over current recognition methods, including feature measurement and detection of life. These enhnaced security measures could have wide-ranging applications in the fields of access management, access control areas, and background checks for the safety and employment purposes.

1.4 Objectives

EEG observes the brain activity exercised in various mental states and mental tasks. In the preliminary stage, we evaluate similarity and dissimilarity between mental task patterns in order to calculate the threshold values needed to design the last step for biometric applications. The purpose of this research is twofold: we hope to investigate the self-similarity and cross-similarity between EEG patterns of two different human subjects and to investigate the potential and viability of using the power spectral density feature to combine the Alpha-Beta rhythm for classification.

1.5 Organization of the Study

This report is organized into six chapters. Chapter 1 reveals the basic concepts of biometrics, biometric applications, biometric identifiers, and electroencephalography (EEG). This chapter also discusses the motivation and objectives behind this experiment and covers a brief outline of the study.

Chapter 2 presents further detailed description on biometrics and EEG, introducing and describing various types of biometric systems based on physical and behavioral characteristics, a concise history of the biometric system, drawbacks of currently used biometry systems, different types of EEG rhythms and recording techniques, the concept of event-related potential (ERP), and a discussion of related studies in these areas.

Chapter 3 explains experimental protocols, data acquisition for the designated mental tasks, and pre-processing. The recorded EEG signal is in a time domain that is contaminated with various artifacts. Then, in the pre-processing stage, the artifacts in the

EEG signals were reduced and the original EEG was extracted by applying DC offset removal method and power line noise removal.

In Chapter 4, the process of extracting combined Alpha-Beta bands from EEG using a band pass filter is explained. Next, Power Spectral Density (PSD) estimation using Burg's method is discussed. The average band power was estimated next, which was later used in the classification process, where self-similarity and cross similarity between EEG patterns using a Euclidian distance classifier were evaluated.

Figure 1.1 illustrates the framework of the overall experimental procedure that will be explained in details in Chapter 3 and chapter 4.

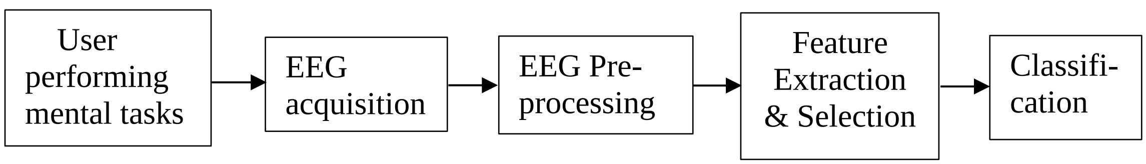

Figure 1.1: Data processing diagram

Chapter 5 summarizes the results of the experiment and discusses the classification performance for the proposed model; and Chapter 6 highlights the primary outcomes of the study, presents the analysis of the results, limiting factors, and potential improvements. In the final chapter, future research that can be conducted to design a practical system using EEG signals for biometric applications is discussed.

Chapter 2

Biometrics and EEG

In recent years, technology has expanded to include a significant number of internationally-used biometric methods. Currently, biometric systems use fingerprints, hand shape, parts of the eye, voice, face shape, handwriting, and keystroke and finger shape for identification and verification. New measurements in development include gait, ear shape, optical skin reflectance, head resonance, and body odor.

Based on how many characteristics would be used, biometric systems could be divided into two categories: unimodal and multimodal systems (Hong, Jain, and Pankanti 1999). Unimodal biometric systems take into consideration only one feature for recognition; for example, face recognition, fingerprint recognition, and iris recognition, whereas multimodal biometric systems usually take into account multiple features obtained from more than one biometric modality, such as fusion information from faces, fingerprints, and others.

2.1 Essential Criterion in a Biometric System

Biometric characteristics should have specific qualities like universality, uniqueness, or, at least, be distinctive, reliable, etc. Biometric characteristics must be:

- Universal—a characteristic every human being possesses.
- Persistent—constant over an extended period; the attribute should not change as a result of age or chronic disease.
- Distinct—the trait must be unique, or at least have a parameter that distinguishes one individual from another.
- Measurable—it should be possible to capture measurements easily in a short time.

- Accepted—the capturing process should be considered acceptable by a large percentage of the population as being harmless and painless.
- Processed—the captured data should be dealt with in a format that can be easily accessed, used, compared, and saved.
- Attributed—the properties of capturing data should ensure high reliability and a low error acceptance rate.
- Privacy—the capturing process should not violate the privacy of the person.
- Inexpensive—a highly secured system is expensive technology. It is desirable to have is security system that is economic.

2.2 Current Use of Traits in Existing and Developing Biometric Systems

2.2.1 DNA Matching (Chemical Biometric)

Human DNA bears a unique structure and traits which make a highly secure and reliable biometric identifier that is accessed through a chemical process. DNA has been used by law enforcement and by various investigation agencies, super-intelligence, and systems that require higher security, like banks, military or intelligence bases, highly secured research labs, etc.

2.2.2 Ear Shape (Visual Biometric)

Law enforcement may identify an individual using the shape of the ear in order to investigate, detect, and verify evidence.

2.2.3 Eye/Iris Recognition (Visual Biometric)

The iris contains rich biometric features which are used to identify an individual; for example, the colored ring around the pupil is distinctive to an individual. Recent technology even permits a device to capture iris information from a distance, without the specific cooperation of the individual.

2.2.4 Eye/Retina Recognition (Visual Biometric)

The patterns of veins in the back of the eye are used for biometric technology. This information, in a multimodal biometric system, is coupled with fingerprint data to obtain higher accuracy. Because these multimodal data are more accurate, various military applications rely on them in order to restrict access to nuclear weaponry or research sites.

2.2.5 Face Recognition (Visual Biometric)

In this authentication or recognition process, facial features or patterns are analyzed in order to verify human identity. Distinguishing elements of the face include geometric patterns, the relative distance between and directions of specific points of the face, and skin texture. The distinctiveness of faces is limited, as it changes naturally due to the aging process.

2.2.6 Fingerprint Recognition (Visual Biometric)

Fingerprints, the ridges and valleys set on the surface tips of a human finger, have long been used as biometric identifiers. These can be collected by sensors, with the cooperation of the subject, or without the knowledge of the subject, they can be found in latency on objects at a crime scene. Forensic applications have relied on fingerprint analysis for over one hundred years.

2.2.7 Finger Geometry Recognition (Visual/Spatial Biometric)

The three-dimensional geometry of the finger is used to determine human identity; image quality is crucial to this type of analysis.

2.2.8 Hand Geometry Biometric (Visual/Spatial Biometric)

The geometric features of the human hand, such as the lengths of fingers and the width of the hand, are sometimes used to identify a subject. Analysis of these characteristics is vulnerable, as hand geometry can change as a result of injury, disease, and even the wearing of jewelry.

2.2.9 Odor (Olfactory Biometric)

An individual's unique body odor is a distinctive feature. We know this because dogs with highly evolved senses of smell have long been used to track a person's scent in order to find him or her. One recent analysis showed that identification of recognizable patterns in each person's body odor has an error rate of fifteen percent; this margin of error includes factors of changeability like stress, mood, disease, or diet change. While this science is not yet as accurate as a dog's sense of smell, science will eventually improve this technology. Some organizations are working on odor characteristics in blood and breath that will detect early signs of colon cancer and leukemia.

2.2.10 Vein or Palm Recognition (Visual/Spatial Biometric)

Vein patterns in the human finger or palm are unique human biometric identifiers.

2.2.11 Voice/Speaker Recognition (Auditory Biometric)

In "gatekeeper" security systems, such as those used in telephone banking, a voice recognition system can verify the identity of a speaker in order to control access. For identification purposes, this technology could be used for determining an unknown speaker's identity.

2.2.12 Behavioral Biometric Traits

An individual's walking style (gait), seated posture, typing speed or mannerisms, and signature writing might be used to determine identity. As these traits lack distinctive features, related technologies have been researched but not developed to the same level as other biometric identification systems.

2.2.13 Newly-Researched Biometric Characteristics

Brain patterns and heart rhythms are newly-researched biometric recognition features. Electrocardiograms (ECGs) record heart rhythms, while electroencephalograms (EEGs) record brain signals.

2.3 Brief History of Biometrics

Biometric science and technology finds its origin in simple ideas developed over hundreds or even thousands of years. Table 2.1 represents the Chronology of Biometric History (Biometric.gov 2016). From the beginning of civilization, humans have used a sort of facial recognition process in order to distinguish between familiar and unfamiliar people, and that process, of course, has become increasingly difficult as the human population has expanded and evolved. Today, we live in a vast, global culture on a planet crowded with over 6 billion people, some of whom would use this to their advantage in terms of "hiding in the crowd." By developing new technology, scientists work to research and develop new biometric ideas and techniques to ensure security at varying levels and under varying sets of demands.

Table 2.1: Chronology of Biometric History (Biometric.gov)

Year	**Description**
1858	First systematic images capture recorded for identification purposes
1870	Bertillon develops anthropometrics to identify individuals
1892	Galton develops a classification system for fingerprints
1936	Proposed an identification concept using the iris pattern
1960	Semi-automated Face recognition started
	The first model of acoustic speech production is created
1963	Fingerprint automation research paper had published by Hughes
1965	Research on Automated signature recognition started
1969	FBI pushes to make fingerprint recognition an automated process
1970	For the first time, Behavioral components of speech are modeled
1974	Commercial hand geometry systems become available for the first time
1976	Developed first prototype system for speaker recognition
1977	Acquisition of dynamic signature information Patent got awarded
1985	Irises are unique concept had proposed
1986	Standard for Exchange of fingerprint minutiae data has published
1988	First, semi-automated facial recognition system is deployed
	Eigen-face technique is developed for face recognition
1992	Biometric Consortium is established within US Government
1994	IAFIS competition is held
1998	FBI launches CODIS (DNA forensic database)
2000	First research paper for the use of vascular patterns for recognition has published
2002	ISO/IEC standards subcommittee on biometric activities begins
2004	First statewide automated palm print database is deployed in the USA

2.4 Drawbacks of Currently Developed Biometrics

Biometric systems offer many advantages; however, each application method contains certain inherent flaws that can cause problems for its user. Changeability is the major drawback of authentication by unique physical or behavioral characteristics. Aging affects our unique, human characteristics, and this can impede the accuracy of voice recognition and fingerprint analysis. Illness and injury are other complicating factors; for example, if a user loses a finger or develops strep throat, those types of analysis can be difficult or impossible.

Environmental noise could possibly create difficulty in a voice recognition system. People may find eye analysis (of the iris or retina) intrusive, or they may have legitimate concerns about the safety of their eyes during the scan. Also ever-present is the threat of lost or stolen data, as databases store an enormous amount of valuable user-identity information. Knowledgeable ne'er-do-wells understand how to outsmart some biometric technology; certain types of local biometric readers fail to detect fraudulent inputs like a gelatin finger that models a legitimate user's fingerprint (e.g. lifted from a glass). Expense is also a concern, as biometrics systems require homes and businesses to install or upgrade to the most recent technology. Finally, people still have many other general concerns about biometrics in terms of personal security and privacy, adaptability to the rate of change in life, scalability, accuracy, and others.

The following set of authentication methods have required address some of the drawbacks outlined above; several known methods meet a subset of these, but none addresses every desired outcome (Thorpe, Van Oorschot, and Somayaji 2005).

- Changeability—the ability to replace authentication information if user information is compromised.
- Shoulder-surfing protection—protection from spying through direct observation techniques, such as looking over someone's shoulder, to obtain access information about a user's PIN or any electronic device password.
- Theft protection—a biometric system which could resist any fraudulent activity.

- User non-compliance protection—biometric information is protected by a form that a user cannot easily share.

2.5 EEG Advantages Over Other Biometric Identifiers

Cognitive biometrics, via a “brain print biometric system,” use a person’s cognitive EEG rhythm to create a unique identifier for privacy protection (Kumari and Vaish 2014). EEG-based biometrics attempt to solve the problem of “what you know” and “what you have” authentication methods by the use of an appealing concept.

EEG identifiers bear specific advantages over conventional ones, and one of those advantages is increased security and privacy protection. Brain signals are not related only to the subject’s genetic information, but also his or her lifetime experience, making them unique to each subject and stable over time. It would be difficult to acquire brain signal biometrics by force, as they are dependent on the mood and stress level of the subject. As brain waves cannot be “exposed” (as in the case of an eye or finger), it would be difficult to fool a verification device. Additionally, brain waves are not shareable, so they cannot be compromised by user non-compliance.

Another advantage of the EEG biometric is that it is highly changeable, and therefore difficult to counterfeit. Brain activity changes as quickly as thought. Biometrics based on physical traits, such as the iris pattern, DNA, heartbeat, fingerprints, and others, are naturally predetermined, so we cannot change them, as we would a password, to increase security. Our brain activity, in these terms, is an ever-changing password that is nearly impossible to replicate.

2.6 Electroencephalography (EEG)

Electroencephalography (*electro*-electrical activity, *encephalo*-of or relating to the brain, and *gram/graph*-written or recorded in image) is a procedure used to record the imaging of brain's electrical activity for the purposes of medical application (Kumari and Vaish 2014). EEG, for short, is one of the most valuable tools available in medicine and in science for examining and diagnosing the brain, its activity, and its pathology.

EEG is the measurement of the electrical potential difference between an electrode and a reference electrode of the human brain when the human brain functions in response to a certain stimulus. EEG is registered in a graphical manner over time, and it can be performed in two different ways (Benbadis et. al. 2008). It can either be recorded directly from the brain through a surgically-implanted electrode placed at particular regions of the human brain; this direct method is referred to as Invasive or Intracranial EEG. It can also be recorded from the surface or cortical layer of the human brain, which procedure is known as Non-Invasive or Extracranial EEG (Benbadis et. al. 2008).

2.7 Related Work

In the last decade, scientists have performed and written some important research on the use of EEG signals in security-relevant applications. Thorpe, Van Oorschot, and Somayaji (2005) introduced the idea for an authentication system using *pass-thoughts* and described the design of such a system in combination with EEG.

Marcel and Millán (2007) proposed the use of Power Spectral Density as the feature and a statistical structure based on Gaussian Mixture Models (GMM) and Maximum Posteriori Model (MAP) adaptation on speaker and face authentication. Poulos et. al. (2001) addressed the idea of person identification based on spectral information extraction. They performed a neural network classification on real EEG data of healthy individuals to investigate experimentally the connection between a person's EEG and genetically specific information. Their classification scores ranged between 80% to 100%, providing evidence that the brain signal or EEG carries genetic information for person identification.

A novel two-stage biometric authentication method was introduced by Palaniappan (2006), in which method he includes both linear and nonlinear measures to improve accuracy in the feature extraction methodology. His research method showed great potential for actual application and also that the method is highly resistant to fraud. As the features have a high level of redundancy, to keep only the most discriminatory features, he used Principal Component Analysis (PCA) for dimension reduction of the feature vector.

More recently, Chang et.al. (2013) developed a model using consumer-grade, single-channel EEG technologies. Their model provides good accuracy for authentication systems that use the low-cost, single-channel EEG sensor.

2.8 Different Types of EEG Rhythms

EEG signals usually comprise various frequency bands. Each band consists of signals related to particular brain activities (Basar et. al. 1995). The regions of a normal human cortex have their intrinsic rhythms in the range of 0.5 Hz to 40 Hz. An EEG recording, in general, shows five main rhythms: Delta (δ) $0.5 - 4$ Hz, Theta (θ) $4 - 8$ Hz, Alpha (α) 8 – 14 Hz, Beta (β) 14 – 30 Hz, and Gamma (γ) over 30 Hz. A detailed characteristic of the sub-bands is given in the following (Ramprakash and Kanniga 2015; Veselis et. al. 2001):

2.8.1 Delta Rhythm (0.5 − 4 Hz)

Delta rhythm is a high oscillatory activity in EEG that is recorded during deep or slow wave sleep (SWS). In SWS, delta waves have relatively large amplitudes (75 $\mu V -$ $200\mu V$) and show strong scalp coherence. Slow delta rhythms dominate in the brains of newborns. An increase in delta pattern activity during performance of a mental task is related to the subjects' increased focus during internal processing.

2.8.2 Theta Rhythm (4 – 8 Hz)

Theta rhythms are dominant in young childrens' brains. In the case of adults, these are sometimes detected in drowsiness, arousal, meditation, or creative activity, so theta rhythms are also nicknamed the "creative" rhythms. Comparing EEG power between resting and mental task performance, we observed, in this study, a Theta band power increase called *Theta-band power synchronization*.

2.8.3 Alpha Rhythm (8 – 14 Hz)

Alpha rhythms are most pronounced in the posterior, central, and occipital regions of the brain. Alpha band oscillations show standard amplitude limited up to 50 mV (peak-to-peak), a level high enough to be clearly observable in raw EEG samples for specific mental states. Alpha waves are induced by having the subject relax with closed eyes, and they are decreased by open the eyes or any stimulus that incites thought.

2.8.4 Beta Rhythm (14 – 30 Hz)

Depending on the performed task, beta rhythms are detectable mainly from the frontal, parietal, and motor regions. Beta activity is a characteristic of increased alertness and focused attention. It is closely related to motor behavior and is sometimes weak with varying frequency during active organ movements, anxious state of mind, and states of concentration or anxiety.

2.8.5 Gamma Rhythm (over 30 Hz)

Gamma rhythm is difficult to register by electrodes placed on the scalp. Though the frequency range usually does not exceed 45 Hz, in the case of electrocorticogram (ECoG), recording components reached up to 100 Hz or higher. Gamma rhythm is predominant for multiple motor behaviors or task performance involving a large population of neurons, such as sensory stimuli recognition, the onset of voluntary movements, and others.

2.9 EEG Recording Techniques

EEG measurement and data recording system contain the following elements:

- Electrodes with conductive media
- Amplifiers with filters
- A/D converter
- Recording device

Signals from the skull surface are found by electrodes (Kondraske 2010) then amplified into a range so that the signal can easily be digitalized. Next, the A/D converter changes the signal from analog to digital, and the signal is saved and monitored by a computer. Voltage difference is weighed between signal electrodes and a reference electrode. If the differential voltage between two active electrodes is taken into consideration, then a third electrode, called a *ground electrode*, is used as a reference.

2.10 International 10–20 Electrode Placement System

This system points out the physical location for the placement of electrodes on the human scalp. The *10-20 System*, an internationally accepted, standardized method of electrode placement on the cortical layer of the brain, is so named for how it considers the anatomy of the skull. The entire cortical region is separated into intervals of 10% to 20% to emphasize the point of an electrode placement. The cerebral cortex is divided into corresponding regions from prominent anatomical points of interest (Castellanos et. al. 2006). 10-20 labels demonstrate relative distance in percentage between auricular and nasal zones, where the actual positions of electrodes are determined. Electrode placement positions are named according to the cortical zones such as: F (frontal), C (Central), T (temporal), P (posterior), and O (occipital), with odd numbers on the left side and even numbers on the right aspect of the head (Blakemore and Frith 2005). Left and right side is established by the general point of view of a human subject.

Different brain areas are determined according to their functions (Zhang and Britten 2011). Each cortical electrode is placed in the proximity of a particular brain center such as:

- F_7 node: near centers for intellectual activities
- Fz node: near centers for intentional and motivational activities
- F_8 node: near the center of emotional impulses.
- C_3, C_4, and Cz nodes: near the center of sensory and motor functions.
- P_3, P_4, and Pz nodes: perception and differentiation of activities.
- T_3 and T_4 nodes: location of emotional activities processors
- T_5 and T_6 nodes: available memory functioning activities
- O_1 and O_2 nodes: near visual functions (Benbadis et. al. 2008).

In Figure 2.1, we have illustrated 32 electrodes placement scheme for the ANT Neuro wave guard cap that have been used to record EEG.

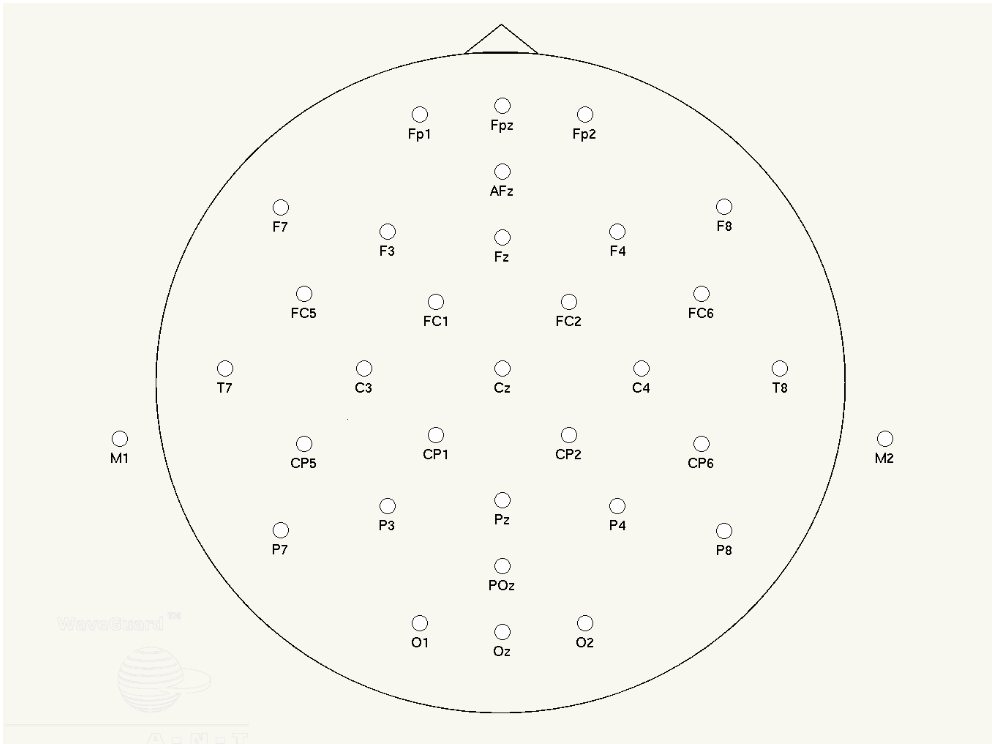

Figure 2.1: 32 Electrodes placement scheme for wave guard cap (ANT Neuro).

2.11 Evoked Potentials (ERP)

Bickford (1987) named ERPs—evoked potentials or event-related potentials—as major potential fluctuations that may result from evoked neural functions initiated by an external or internal stimulus. ERPs are a suitable methodology for studying the different factors of cognitive processes of both normal and abnormal nature, like neurological or psychiatric disorders (Picton 2000). For mental operations that take place over time, such as perception, selective attention, language processing, and memory, ERP analysis is an excellent method of defining the time course of these activities. ERPs are unrecognizable from raw EEG samples, as ERP component amplitude is often much smaller than that of

EEG traces. ERPs are extracted from a set of single recordings by digital averaging of recording periods called *epochs* of EEG, time-locked to repeated occurrences of sensory, cognitive, or motor events (Gevins and Rémond 1987). Continuous background EEG fluctuations are averaged out, leaving the event-related brain potentials (Gevins and Rémond 1987).These electrical signals reflect only the activity with the stimulus functioning in a time-locked way. The ERP thus reflects, with high temporal resolution, the patterns of neuronal activity evoked by a stimulus (Teplan 2002).

Chapter 3

Experimental Protocols, Data Acquisition and Pre-processing

Our objective in performing this experiment is approach developing a pattern recognition system utilizing EEG signals. By placing electrodes on the scalps of the subjects, we detected and accumulated electrical changes, as EEG waves, from a large number of synapses (neurons) in the cerebral cortex. Once the activity of the neural structure decreases, brain waves become partly synchronous; therefore, we detected some distinct wave features, such as δ (0.4-3Hz), θ (4-7Hz), α (8-13Hz), and β (14-30Hz). Specifically, the α and/or β waves are applicable in biometric recognition.

3.1 Mental Tasks

We created mental tasks for this experiment from the perspective of neuroscience: mental arithmetic, mental rotation of a three-dimensional block, and so on. For our experiment, we selected two mental tasks in order to acquire EEG signals, a mathematical task and an imaginative task. In the math task, or numerical sequencing task, we asked the subjects to count a sequence of numbers in any desired order; for example, in arithmetic sequence, geometric sequence, the Fibonacci series, the Square series, etc. In the imaginative task, we asked subjects to imagine a color and then to think about whether they like or dislike the color.

3.2 Data Acquisition System

ANT Neuro, a Netherlands-headquartered medical technology solutions company, uses its ant™ and eego™ software systems to record non-invasive electroencephalography by using eevoke™, an EEG/ERP recording system. According to the ANT Neuro Manual, the procedure can be configured within 24 to 246 channels.

eevoke™ creates for the subject presentations that are auditory, visual, or a mix of those by presenting sound, image, or a movie, for example. **ee**voke™ controls the presentation through scenarios that contain information regarding the timing and event codes of multimedia files and define the sequence of tribulations and blocks in the experiment (www.ant-neuro.com/products/eevoke). Each presentation and corresponding management info square measure are taken in real time, leading to a complete and versatile atmosphere for experiments (ANT Neuro).

3.3 Data Recording Time

We created a four-minute scenario presentation by using **ee**voke™ to design a necessary trigger that stimulates the signal needed for the biometric system.

Table 3.1: Summarization of The EEG signal acquisition protocols that has used in this current study

Mental Tasks	**Timeline(s)**
Subject Resting	2 min
Numerical sequence counting	20 seconds
Subject think about color	20 seconds

3.4 Data Acquisition

We set out to collect data from a minimum of two test subjects, where we will instruct each one to perform all mental tasks while relaxed and without blinking, eyeball movement, eyebrow contraction, or muscular movement. This kind of movement, referred to as artifacts, contaminates the EEG signal. Each test subject will perform two tasks for a minimum of twenty seconds. We will repeat the recording session twice for each subject. The first recording will be of the training set, and the second session will be of subjects testing in the classifications stage. We used MATLAB simulation software load EEG data and develop the necessary code to process EEG data pattern recognition.

3.5 Extracting EEG fragments of interest

In order to determine which segment of the data sample we need to take into account for further processing, we use the recorded “trigger file” information, which contains time-related information about when the trigger fired. A ten-second segment of data samples for the math task response has been extracted from the entire set of EEG data samples for every single channel. The same process was also applied to the imagination task response. From the recorded EEG signals, the M_1 and M_2 electrode have not recorded any data signal, so the sample data only contain thirty electrodes recording signals. A total 2561*30 data samples for each task response has been extracted and plotted using necessary Matlab commands. In Figure 3.1 we have plotted EEG samples for the desired 10 seconds in the F_3 channel.

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Figure 3.1: Extracted Raw EEG for channel F_3

From Figure 3.1, we observe the ten-second extracted raw EEG data where the X-axis represents the samples number, and the Y-axis represents EEG signal amplitude in microvolts. The high amplitude spikes may indicate the presence of biological artifacts.

3.6 Artifacts in raw EEG signals:

EEG data contamination could occur at many points during the recording process. These unexpected and unavoidable noises from different sources are defined as artifacts. Externally generated artifacts, such as line noise and DC offset voltage, which are prominent during EEG recording, could be decreased by taking necessary hardware measures, but, for biological artifact removal, need software-based processing. Figure 3.2 shows waveforms of some of the most common EEG artifacts which are described later.

3.6.1 Ocular artifacts

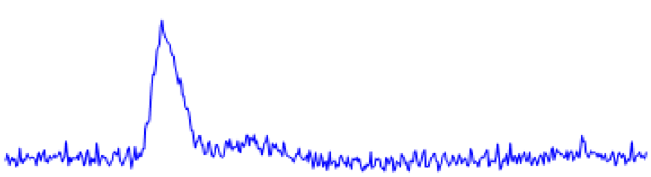
Ocular artifacts usually originate from eye blinking, eyeball movement, and eyebrow contraction (Brown et. al. 2006). As shown in Figure 3.2(a, b), they usually appear as sudden high spikes in the waveforms and are therefore clearly visible (Jung et al. 1996, Jung et. al. 2001). Because of its high amplitude, an eye blink can corrupt data on all electrodes, even those at the back of the head (Patil and Pawar 2012). Temporal filtering, independent component analysis, principle analysis, etc. could help to remove these types of artifacts.

3.6.2 Power-line noise

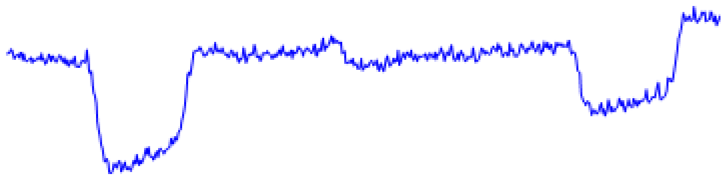
Strong harmonic signals from A/C power supplies can corrupt EEG data as it is transferred from the scalp electrodes to the recording device (Knight 2003). Therefore, it may considerably contaminate the weak EEE signal from the human subject (Benjamin 2001). For example, in Figure 3.2(c) we have illustrated an EEG signal affected by 60Hz power line noise. A notch filter centered at AC line frequency is very effective to remove this noise.

3.6.3 Muscular movement:

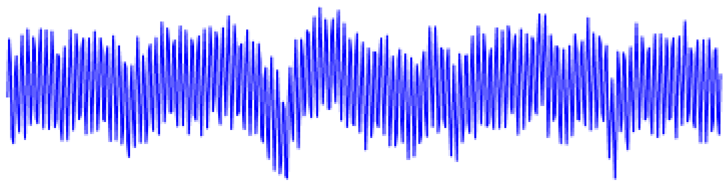
Accidental limb, neck, and facial movements (Jung et al. 1996) usually cause muscular activity in the EEG. These signals have a wide frequency range and can be distributed across different sets of electrodes depending on the location of the source muscles (Knight 2003). In Figure 3.2(d), we have shown EEG signals contaminated by muscular movement artifacts.



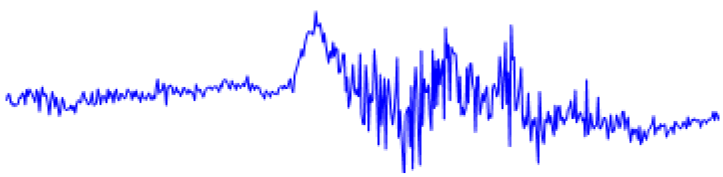
a) Eye blink



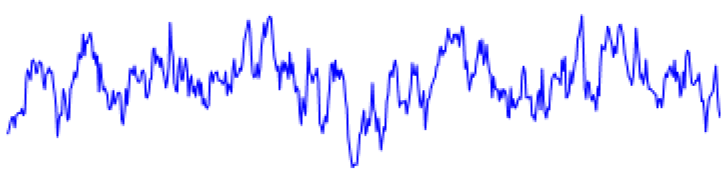
b) Eyeball movement



c) 60Hz Power Line Noise



d) Muscle activity



e) Clean EEG

Figure 3.2: Different types of common artifacts patterns in EEG (Knight 2003).

In Figure 3.2 (a,b,c,d), we see EEG signals affected by various types of artifacts. Each artifact produces a unique signal pattern. The latter may help us to visually recognize the artifacts in EEG recordings, and sometimes, the contaminated trials or segments may simply discarded. Figure 3.2 (e) illustrates an EEG signal with no artifacts.

3.7 Data pre-processing

Ocular artifacts, DC offsets, power-line noise and related artifacts are also visibly detectable in “noisy” EEGs. Various approaches exist to reduce nice contaminations in noisy EEG; such processes are referred to as signal pre-processing. Pre-processing may vary depending on the purpose of the experiments. Figure 3.3 summarizes the pre-processing steps we followed for this experiment.

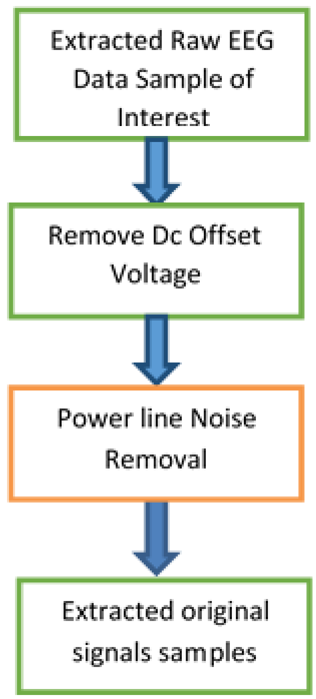


Figure 3.3: Block diagram of pre-processing steps

The preprocessing steps showed in Figure 3.3 are described in details below.

3.7.1 DC offset removal:

By subtracting the mean for each channel from all data samples in the respective channel, DC offset can be removed from the EEG data. Figure 3.4 illustrates the channel F_3 EEG signal with and without DC offset voltage.

Figure 3.4: Sample EEG of channel F_3 with (top) and without (bottom) DC offset voltage

In the top panel of Figure 3.4, we can see that the ten-second raw EEG data are contaminated by the DC offset voltage. Subtracting the mean has removed the contamination, shown in the bottom panel. We can note the change in the amplitude scale that indicates DC offset removal. However, other artifacts are still present in EEG.

3.7.2 Power-line noise removal:

An FIR band-stop filter was designed in MATLAB to remove 60Hz power-line noise from the EEG signal for every channel of sampling frequency 256 Hz. The filter specifications are shown in Table 3.2.

Table 3.2: Specifications of the FIR stop band filter to remove 60Hz power line noise

Fs (Sampling Frequency)	256 Hz

$Fpass_1$ (lower stop-band frequency)	59.5 Hz
$Fpass_2$ (upper stop-band frequency)	60.5 Hz
Filter order (N)	500

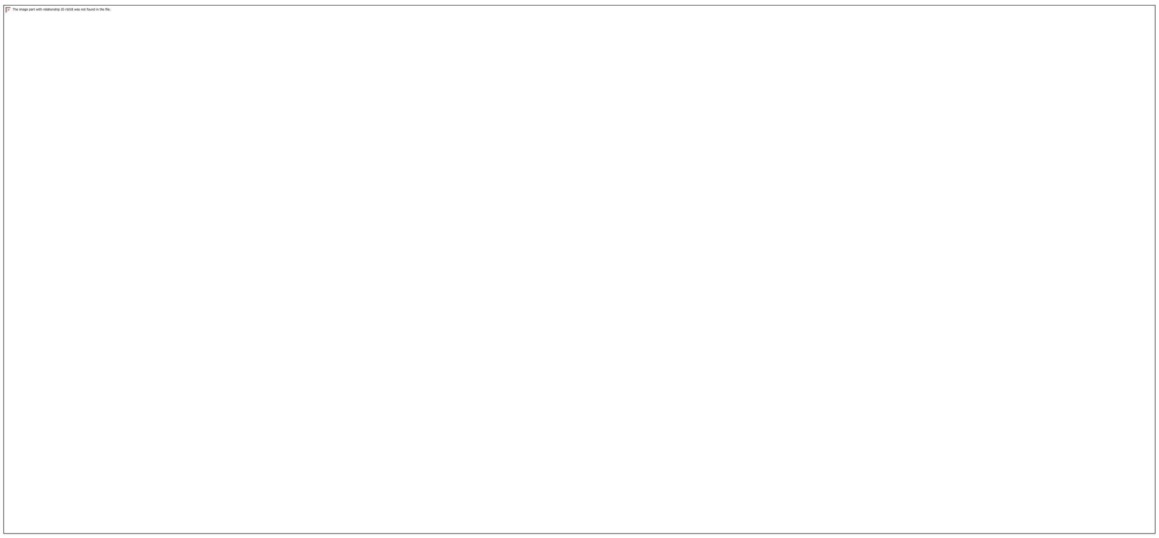


Figure 3.5: Sample EEG for channel F_3 with 60 Hz noise (a), without 60 Hz noise (b), and after discarding the filtering time delay (c).

In Figure 3.5, the x-axis represents the sample number, and the y-axis represents signal amplitude in microvolts. Figure 3.5 (a) shows an EEG signal with power-line noise, Figure 3.5 (b) shows how it changed after using the FIR stopband filter. A one-second time delay has been introduced by the filter, which has been discarded and plotted in Figure 3.5 (c).

Chapter 4

Feature Extraction and Verification

Using human subjects, we underwent several trials to record EEG data in the laboratory. The recorded EEG in the laboratory is often high-dimensional that may difficult to analyze directly with the classification tools of choice (Fowler 1997; Gamma 1997).

In this chapter, we will further process the EEG signals to extract the PSD feature to use for pattern recognition. We have illustrated the processing steps using a block diagram in Figure 4.1 below, which will be explained shortly.

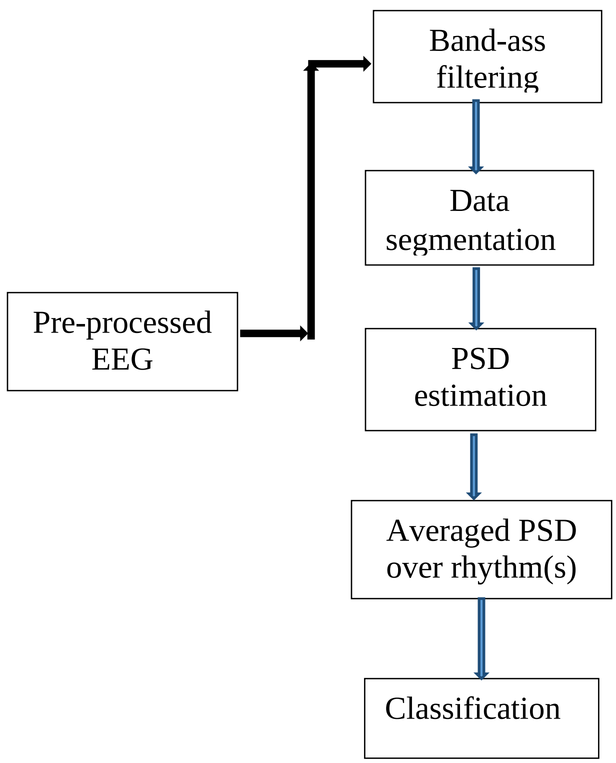


Figure 4.1: Data processing block diagram.

From Figure 4.1, we can see that to evaluate the PSD, we first have to extract the desired combined Alpha-Beta frequency band by using a band-pass filter. Next, the dataset must be segmented into nine parts, each containing 1 second of data. Every segment of data contains a total of 256 samples for each channel. For each segment, the power spectral density must be estimated in the feature extraction stage. The average Alpha-Beta band power can be evaluated for each electric node using PSD estimations over a specific band. Finally, for the classification process, we will use a Euclidian distance classifier and make decisions.

4.1 Bandpass Filter

To smooth our waveform and extract the frequency band of our interest and discard all other frequencies, we have used a bandpass filter. We have selected a Finite Impulse Response (FIR) Filter of the Chebyshev window type. FIR filters are beneficial for cleaning up noises from EEG data because they do not require feedback, they do not take into account iterative errors, and they are easy to implement.

Table 4.1 summarizes the specifications to design our filter of interest. We have selected the bandpass-type FIR filter to extract the Alpha-Beta rhythm (8-30Hz) from the EEG and to reject all other artifact frequencies.

Table 4.1: Specifications of the FIR Chebyshev band-pass filter.

Fs (sampling frequency)	256 Hz
Fpass1 (lower pass-band frequency)	8 Hz
Fpass2 (upper pass-band frequency)	30Hz
Stop-band attenuation (R)	40 dB
Filter order (N)	650

Figure 4.2 illustrates the EEG signal before and after applying the band-pass filter on F_3 channel data to extract Alpha-Beta rhythm.

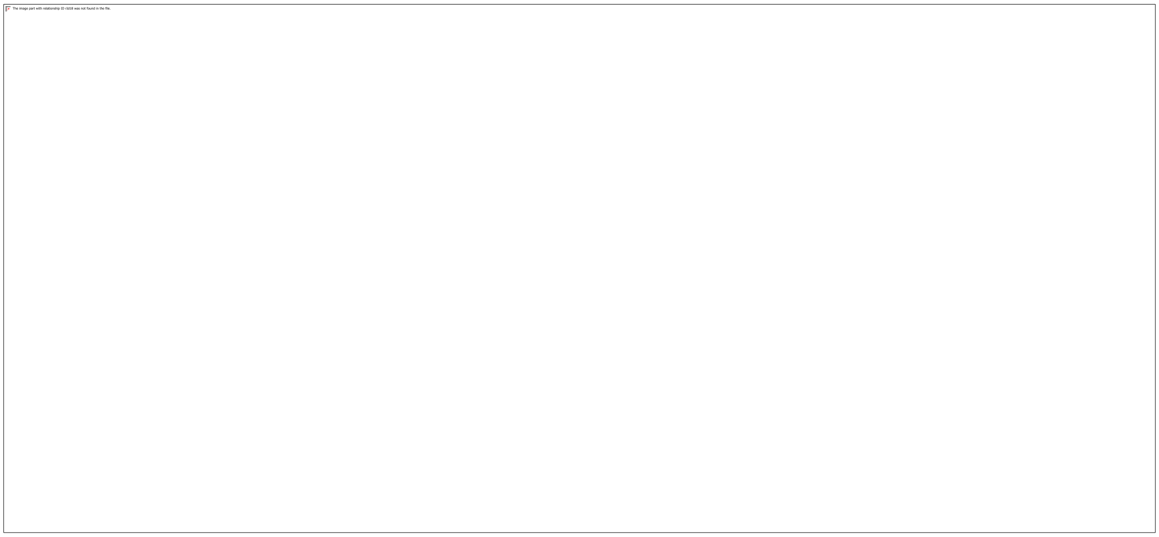


Figure 4.2: Original EEG for the F_3 channel (a), filtered EEG over the combined Alpha-Beta rhythms (b), filtered EEG after discarding the filtering time delay (c).

In Figure 4.2, the x-axis represents time in the secons, while the y-axis represents the signal amplitude in microvolts. We observe that EEG amplitude has decreased significantly after using a band-pass filter.

4.2 Data segmentation

Data segmentation prior to PSD estimation is necessary because of the non-stationary nature of EEG, where the concept of the power spectrum is not applicable. Only short fragments of EEG can be viewed as locally stationary for PSD estimation. After time delay data removal by bandpass filtering, we have eight seconds of data remaining. We have divided these data into eight segments, each containing 256 data samples. After segmentation, DC was removed by subtracting the mean from each sample for each segment separately before further analysis.

4.3 Power Spectral Density

In terms of distinguishing one person from another, Power Spectral Density (PSD) is the most critical feature of the EEG signal. PSD shows us how power is distributed over the frequency.

In the present work, Burg's method was implemented to evaluate PSD for each segment of the EEG data.

4.3.1 Burg's method

Burg's method for PSD estimation is similar to the Modified Covariance method. It conventionally operates on the time series data using iteration to find a reflection coefficient, and it finds a set of all-pole model parameters to minimize forward and backward prediction error vectors. A teacher at the University of Western Australia mentioned in his book about advanced control and signal processing that Burg's algorithm is less accurate than the Modified Covariance method, as it performs the minimization sequentially on the reflection coefficients for the sake of stability (Zaknich 2006).

4.3.2 AR model order selection

An important issue in AR modeling is the selection of the appropriate model order. An underdetermined order amy result in a smoothed spectral estimate with a poor resolution, whereas an overdetermined order could cause spurious peaks in the spectral estimate and lead to spectral line splitting.

Commonly used criteria for model order selection include Akaike Information Criterion (AIC), Schwarz-Bayes Criterion (SBC), also known as the Bayesian Information Criterion (BIC), Akaike's Final Prediction Error Criterion (FPE), and

Hannan-Quinn Criterion (HQ) (Schlögl 2000). In brief, each criterion is a sum of two terms: one is the prediction error of the model, and the second term is the number of freely estimated parameters in the model, which increases with increasing model order (Swartz Center). We need to minimize both terms by selecting an appropriate model order to gain estimation accuracy and efficiency.

According to the finite sample theory and Levinson-Durbin recursion analysis, the order selection depends on the reflection coefficients as the selection criteria, since the decrease in the residual variance is related to reflection coefficients (Jones 1976; Broersen 1985). Model order overestimation could be determined from the significant decay of reflection coefficient value towards zero. In this experiment, the model order varied for different segments and channels. Previous reports concluded that, to avoid overestimation or inadequate estimation, it may be beneficial to select different orders for different segments rather than use the average model order for different segment data (Engin, Ünsal, and Engin 2006).

4.3.3 PSD estimation

Two built-in MATLAB functions were used to estimate the PSD for each data segment. First, *arburg* was used to determine the approximate AR model order using the reflection coefficient. Second, *pburg* was used to estimate PSD for the current data segmant with the previously selected model order “p”.

In our experiment, for different channels and segments, AR model order was varying from 5 to 13.

4.4 Average PSD estimation for Alpha-Beta rhythm

Average PSD estimations have been conducted corresponding to the Alpha-Beta frequency range (8 - 30 Hz). So for every channel and every EEG segment, one average PSD was estimated. Considering eight EEG segments and that each segment contains 30 channels, the total of 8*30 average PSD estimates were produced and used as the classification features. For our experiment with two subjects and two tasks, eight 30-dimansional vectors were used in the classification.

4.5 Euclidean distance classification

Euclidean minimum distance classification is a pattern recognition technique based on matching an unknown input with the predefined data patterns. In this method, an input with the unknown pattern is assigned to the class to which it is closest regarding Euclidean distance (Gonzalez and Woods 2008, 698). It estimates the Euclidean distance between the unknown input and each of the predefined prototype pattern vectors. Then it chooses the minimum distance to make the decision of assigning the unknown input to one of the prototype pattern vectors. Euclidean distance-based classifications are popularly used in numerous applications including image recognition, statistical analysis, DNA sequencing, etc. (D'Agostino and Dardanoni 2009). In Cartesian coordinates, if p = (p_1, p_2...,p_n) and q = (q_1, q_2,..., q_n) are two points in Euclidean n-space, then the distance (d) from p to q, or from q to p, is specified by the Pythagorean formula (Greenacre 2008):

$$d(p,q) = d(q,p) = \sqrt{(p_1 - q_1)^2 + (p_2 - q_2)^2 + \cdots + (p_i - q_i)^2} = \sqrt{\sum_{i=1}^{n} (p_i - q_i)^2} \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots (4.1)$$

In the Euclidean distance classifier, the training set is provided to build up a model, and the testing set is provided as an input to validate the model built. EEG data was recorded from two different subjects for two different tasks. One EEG set from each subject was used as the training set for the classifier and the other set was used as the testing set. The classification results are presented in the next chapter.

Chapter 5

Results and Discussion

5.1 Power Spectral Density estimation

In Figures 5.1 and 5.2, PSD estimates are illustrated for two different subjects corresponding to two different tasks for a one-second fragment of the O_1 channel EEG.

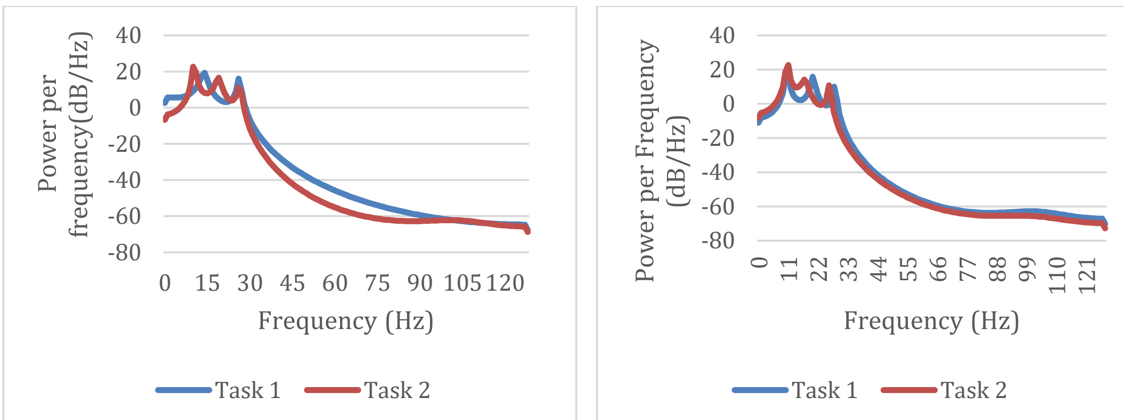


Figure 5.1: PSD estimation of EEG in O_1 channel for subject 1 (a) and subject 2 (b) corresponding to different mental tasks.

Figure 5.2: PSD estimation of EEG in O_1 channel for two subjects and corresponding to "math" (a) and "color imagining" (b) tasks.

As seen in Figure 5.1 (a) and (b), PSD estimates in the O_1 channel EEG corresponding to two different mental tasks for subject 1 and subject 2, respectively. For subject 1, the selected AR Model order was 5 and 8 for the math and the imaginative tasks, respectively. We observe two peaks in the PSD plots for the math task that correspond to 14 Hz and 26 Hz; and for the imaginative task three spectral peaks are observed at 10 Hz, 19 Hz, and 26 Hz. For subject 2, three peaks occurred in the PSD plots for the math task at 11 Hz, 20 Hz, and 24 Hz; and three peaks at 11 Hz, 17 Hz, and 26 Hz correspond to the imaginative task. For both tasks, the AR model order was 8. From Figure 5.1, we can visualize how the PSD over different frequency ranges differs for different activities, even in the same subject.

From Figures 5.2 (a) and (b), we can see how the PSD estimates vary for different subjects performing the same task. For the math task, AR model order was 5 for subject 1, and two peaks are observed at 14 Hz and 26 Hz. For the same task performed by subject 2, three peaks have occured at 10 Hz, 19 Hz, and 26 Hz for AR model order 8. For the imaginative task, subject 1 showed three peaks at 11 Hz, 20 Hz, and 24 Hz for model order 8; and for subject 2, three peaks occurred at 11 Hz, 17 Hz, and 26 Hz for the model order 8. We can conclude that the power distribution over frequency may be different for different subjects performing the same task. As the PSD values vary by task and subject, from the classification stand point, we suggest using PSD as a potential biometric discrimination feature.

Since the model order varied between 5 and 13, we observe that for higher model order, the number of peaks usually increase. For the subjects' PSD plots, the Alpha band peaks have higher power amplitude than the Beta band peaks for every task, where a Beta band contains more than one peak for higher AR model order.

Next, the average PSD were estimated for each EEG segment and for thirty channels. The average PSD were represented as 30-dimansional vectors and used as the classification features.

5.2 Classification

Our experimental objective was to find out the EEG patterns' similarity and dissimilarity for different mental tasks for the same subject and different subjects, assessing which data could be used for biometrical applications, such as authentication and verification.

In the classification stage, we have evaluated the Euclidian distance between two thirty-dimensional vector pairs. In the present experiment, two sets of data for each mental task by a single subject were generated; one set was used as a training pattern and the other one as the testing pattern. Therefore, for two different subjects and two tasks, a total of eight vectors were produced. The Euclidian distance between a training pattern and the testing pattern was evaluated for the same subject and between different subjects for the same task. According to the minimum distance classifying rule, the pattern with the minimum distance will be classified to the same group as the training set. The classification results are presented in Table 5.1 for subject 1 and in Table 5.2 for subject 2, where

D_{11} – Euclidian distance between the subject 1 training pattern and the subject 1 testing pattern;

D_{12} – Euclidian distance between the subject 1 training pattern and the subject 2 testing pattern;

D_{22} – Euclidian distance between the subject 2 training pattern and the subject 2 testing pattern;

D_{21} – Euclidian distance between the subject 2 training pattern and the subject 1 testing pattern;

D_{min} – minimum Euclidian distance

Table 5.1: Classification results for subject 1.

	D_{11}	D_{12}	D_{min}	Classification result	Classification status
Math Task	73.31	49.85	49.85	Subject 1 and Subject 2 are the same	Wrong decision
Color Imagining Task	72.71	31.10	31.10	Subject 1 and Subject 2 are the same	Wrong decision

Table 5.2: Classification results for subject 2.

	D_{22}	D_{21}	D_{min}	Classification result	Classification status
Math Task	35.80	66.82	35.80	Subject 2 and Subject 2 are the same	Correct decision
Color Imagining Task	50.02	77.78	50.02	Subject 2 and Subject 2 are the same	Correct decision

From Table 5.1, we observe that for subject 1 used as the test subject, the minimum distance classifier failed to classify the same subject pattern for both tasks, since for both mental tasks, D_{12} is smaller than D_{11}. From Table 5.2, we observe that in the subject 2 used as the test subject, the classification results are correct for both tasks, since D_{22} is smaller than D_{21}. Therefore, the overall classification accuracy is 50%, which is clearly not sufficient for any practical applications.

Chapter 6

Conclusions and Future Work

6.1 Conclusions

In this experiment, the potential of using EEG as a biometric identifier for biometric authentication and verification was explored. The parametric power spectral density estimates were assessed as unique EEG features for biometric pattern recognition.

The highest classification accuracy of 100% was observed for subject 2 for both mental tasks, although the subject 1 was misclassified for both tasks. The overall classification accuracy was 50%. Although classification accuracy was not sufficient for any practical applications, we believe that EEG-based biometrics is still possible.

We have observed that the alpha rhythm spectral power dominated the beta rhythm power. Perhaps, using the dominant rhythm only for different tasks might improve the classification accuracy.

Another limitation of the reported study is a small participant poll with only male subject's present. Also, participant's age and cultural background were similar. Therefore, the reported results should be viewed as rather preliminary, since EEG data need to be collected (and analyzed) from a considerably bigger and more diverse participant population, as well as with more diverse stimulation, to make definite conclusions regarding the viability of EEG for biometric applications.

6.2 Future Work

In this experiment, EEG signals have been recorded from two subjects for two different tasks to evoke their emotional responses. More subjects and various stimuli patterns, for example, audio and video stimuli, could be used to record a vast variety of

EEG database for the analysis. The power spectral density (PSD) was used as a classification feature of EEG for biometric authentication. Other EEG-based metrics could be extracted from the recorded EEG and investigated for the possibility of using them as EEG features for biometric authentication. A combination of two or more EEG features can also be assessed for biometric authentication. PSD estimations from separate EEG rhythms or a different combination of two or more EEG rhythms can also be attempted for an EEG-based biometric authentication system. Perhaps, a practical system would include the combination of facial recognition, fingerprints, or any other conventional biometric identifier along with the EEG-based authentication. We also could investigate whether the biometric feature could show variation based on gender, age, subject background, culture, etc. Different classification tools or approach might also increase accuracy.

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