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FIRAT UNIVERSITY
GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

INVESTIGATION OF FEATURE EXTRACTION METHOD FOR EEG SIGNAL PROCESSING

Student: Dindar Issa SAEED

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Department: Computer Engineering
Supervisor: Assist.Prof.Dr. Ahmet Çinar

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DINDAR ISSA SAEED

151129119

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(Title of Juror, Name and L/Name and institution):		Sign
Supervisor: **Assist.Prof.Dr. Ahmet Çinar**	**/ Firat Uni. / Comp. Eng.**	
Other Jury Members: **Assoc.Prof. Fatih TALU**	**/ İnonü Uni. / Comp. Eng.**	
Other Jury Members: **Assoc.Prof. Burhan ERGEN**	**/ Firat Uni. / Comp. Eng.**	

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DINDAR ISSA SAEED

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ABBREVIATIONS

(BCI)	Brain Computer Interface
(EEG)	Electroencephalography
(TDF)	Time Domain Features
(FDF)	Frequency Domain Features
(FFT)	Fast Fourier Transform
(WT)	Wavelet Transform
(CWT)	Continuous Wavelet Transform
(DWT)	Discrete Wavelet Transform
(PSD)	Power Spectral Density
(AR)	Autoregressive
(SNR)	Signal-to-Noise Ratio
(MRI)	Magnetic Resonance Imaging

ABSTRACT

INVESTIGATION OF FEATURE EXTRACTION METHOD FOR EEG SIGNAL PROCESSING

Today, in view of human on the computer in most fields, communication has to be documented between human and computer to farther to be done by keyboard or mouse, like brain computer interface (BCI) technique. Since the brain is a very complicated and accurate device, signals emitted from it are different. on that, the signals classed into several types like Electroencephalography (EEG), the cheaper and easiest to use, and from this point, the (EEG) was chosen in this research. To be able to use the (EEG) for BCI technique we need to several steps for signal processing, and the most important step in this process is feature extraction technique, as for feature extraction technique, it can be done by a variety types of methods like Fast Fourier Transform (FFT), Wavelet Transform (WT), Eigenvectors, Time-Frequency Distributions, and Autoregressive Method(AR). In this thesis, we explained what is brain computer interface and for what it's important uses and how we can use, and also we have explained (EEG) signals and feature extraction methods uses to (BCI).

KEYWORDS: Brain computer interface (BCI), Electroencephalography (EEG), Features Extraction, Fast Fourier Transform (FFT), Wavelet Transform (WT), Eigenvectors, Time-Frequency Distributions, Autoregressive Method (AR).

ÖZET

EEG SİNYAL İŞLEMİ İÇİN ÖZELLİK EKSTRAKSİYON YÖNTEMİNİN İNCELENMESİ

Günümüzde bilgisayar ile alakalı birçok alanda kullanılan insan ve bilgisayar arasındaki iletişim, beyin bilgisayar arayüzü (BCI) tekniği gibi yöntemler kullanılarak, klavye veya fare ihtiyacından uzaklaşacak şekilde belgelenmektedir. Beyin çok karmaşık ve düzenli şekilde çalışan bir cihaz olduğu için, buradan yayılan sinyaller çok çeşitlidir. Bundan dolayı, Elektroensefalografi (EEG) gibi daha ucuz ve kullanımı daha kolay olan çeşitli tipler olarak sınıflandırılan (EEG) sinyalleri bu araştırma için seçilmiştir. BCI tekniği üzerinde (EEG) sinyallerini kullanabilmek için sinyal işleme sürecinde birkaç aşamaya ihtiyacımız vardır ve bu süreçteki en önemli adım olan özellik çıkarma tekniği için çeşitli özellik çıkarma tekniklerinden birkaçı olan, Hızlı Fourier Dönüşümü (FFT), Dalgacık Dönüşümü (WT), Özvektörler, Zaman-Frekans Dağılımları ve Otoregresif Metot (AR) gibi yöntemlerden faydalanılmaktadır. Bu tez çalışmasında, beyin bilgisayar arayüzünün nasıl olduğunu, önemli kullanım şekillerinin neler olduğunu ve bunları nasıl kullanabileceğimizi açıklamaktayız ve ayrıca (EEG) sinyallerini ve özellik çıkarım yöntemlerini (BCI) belirtmekteyiz.

ANAHTAR KELİMELER: Beyin bilgisayar arayüzü (BCI), Elektroensefalografi (EEG), Özellikler Ekstraksiyonu, Hızlı Fourier Dönüşümü (FFT), Dalgacık Dönüşümü (WT), Özvektörler, Zaman-Frekans Dağılımları, Otoregresif Metot (AR).

.

1. INTRODUCTION

Human wants to use many components to control computers such as the traditional input devices (keyboard, mouse, pen… etc.). But not everyone can use them on a daily basis, like people with special needs can't use those devices because physically disabled people can't use their limbs to control such devices especially when they require a mouse or keyboard. In this contemporary there are many techniques helped the human to solve those problems and make direct connection between human or animals and computers like brain computer interface(BCI).

Thanks to the growing capacity of computers over time, and the increased ability to perform information processing and storage, it seems that some ideas classified as "science fiction" will become a reality over time, and some have already become a reality, through our thoughts and our brain, without physically touching them.

1.1. Brain computer interface (BCI):

BCI is a new communications technique that can use to communicate between human and computers by using human brain waves, in recent years, this technique has a great aim to control external devices. Brain Computer Interface (BCI) has been considered as another communication channel that uses brain activity that is reflected by electrical, magnetic or hemodynamic brain signals to control many devices, such as computers, robots, video games and people applications with special needs without direct physical movements [1,2,3].

BCI also sometimes called brain machine interface(BMI) is a technique that read mind wave and translates it into some commands to control external devices such as computers. This technique has many applications like a new way for gamers using their heads to play video games without using their limps, controlling robots, controlling artificial limbs, helping people with partial or total disability to use smart devices and helping them to understand more about brain activity and human neural networks [4].

The BCI is not only used for humans but also can use for animals. This technique was tested on a monkey in 2008 and it was capable to control and move the screen cursor over and control the robotic bracket. The capitalize of this study is to understand how animals can reflect for doing something and realize their minds as well [5].

1.2. BCI Structure:

BCI systems seems any other message and control system, has an input, output and other components that translate from input (brain signal) to output (device commands) (Bashashati et al., 2007). BCI systems consist of the following structure see Figure (1.1) [6]:

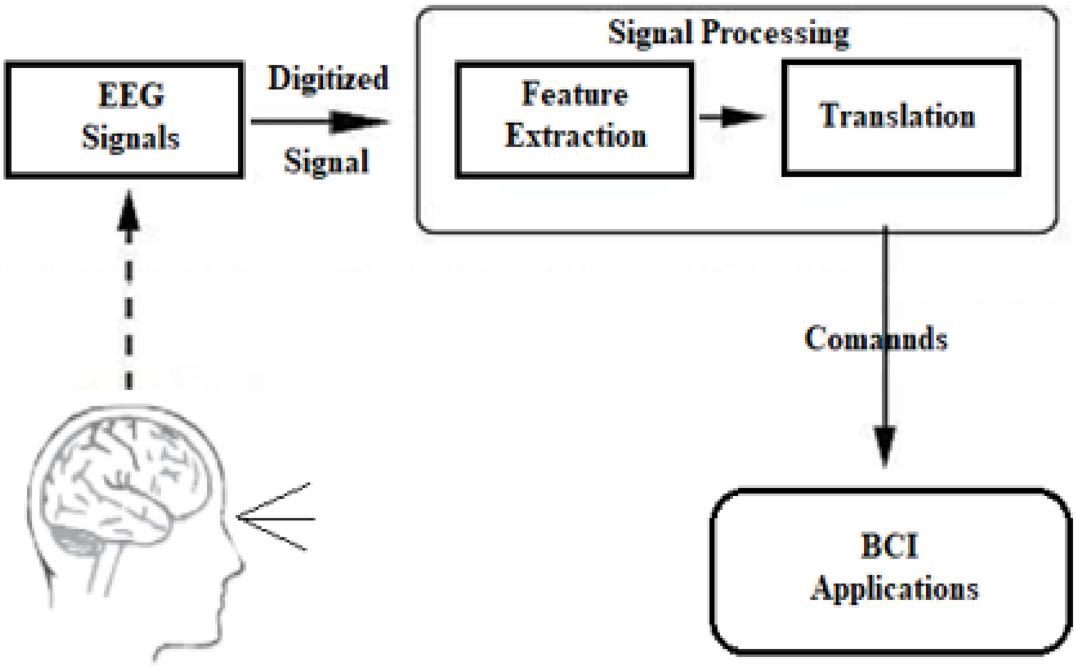

Figure 1.1: BCI Structure.

1.3. BCI Approaches:

It is known that each region of the brain has specific functions (there is an area responsible for memory, one for terminal movement, etc.). The interface of the brain and computer is mainly based on measuring brain activity to see what the user is currently thinking. Two types of brain activity can be monitored:

Electrophysiological activity: It is generated by electrical chemical transmitters when information is exchanged between neurons. Neurons generate ionic currents flowing within and across neural complexes. The methods are used to measure this activity can be divided into:

1- **Surgical methods:** A thin electrode matrix is implanted inside the skull, so there are many risks in these ways. It is worth mentioning that many researches distinguish between two types of surgical methods: (a) Invasive surgical methods, where the matrix of electro-electrodes in the gray matter is implanted in the brain, (b) Partially-invasive surgical methods, the skull remains outside the brain or gray matter, giving higher accuracy than the methods that do not require surgery but with less risk than unfair surgical methods [7].

2- **Non-invasive methods:** In which the brain activity is recorded by external devices without performing any operations (such as placing electrode electrodes on the scalp or using magnetic resonance imaging), there is almost no risk in these methods but less accuracy than Surgical methods [7].

Dynamic blood response: A process in which blood delivers glucose to active neurons at a rate higher than those of inactive neurons. The delivery of glucose and oxygen through the blood stream of the active cells results in an excess of oxy hemoglobin in the vessels of the active region and therefore a significant change occurs between the localized ratio of oxy hemoglobin to dioxin hemoglobin [8]. The methods used to measure this change are indirect, because they measure the dynamic blood response (as opposed to electrical physiological activity) rather than directly correlating with neuronal activity.

There are three types of BCI such as follow:

1.3.1. Invasive BCI:

It is one of the BCI devices and this device has some advantages and disadvantages shown in below as list and see Figure (1.2):

- Uses for those people with paralysis.
- It is connect directly Implanted into the grey matter.
- It has highest signals quality.
- Build up the Scar tissue.

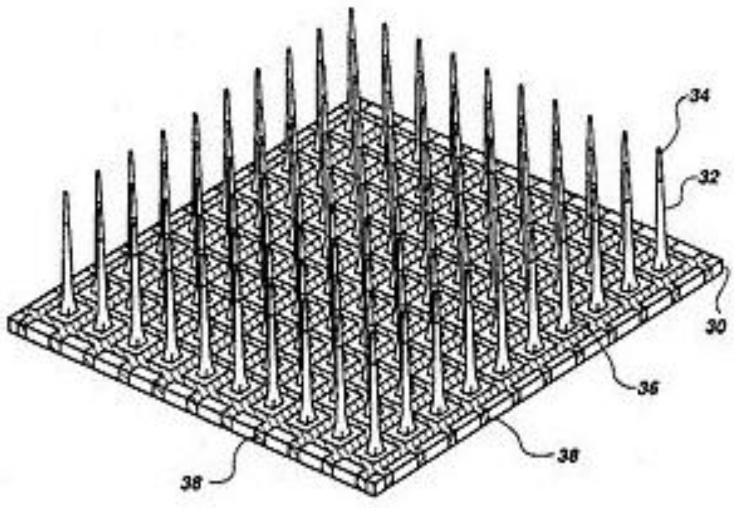

Figure 1.2: Invasive BCI [8].

1.3.2. Partially Invasive BCI:

- BCI apparatus are implanted inside the skull.
- It has signals with better resolution.
- Lower risk of forming scare tissue, see Figure (1.3).

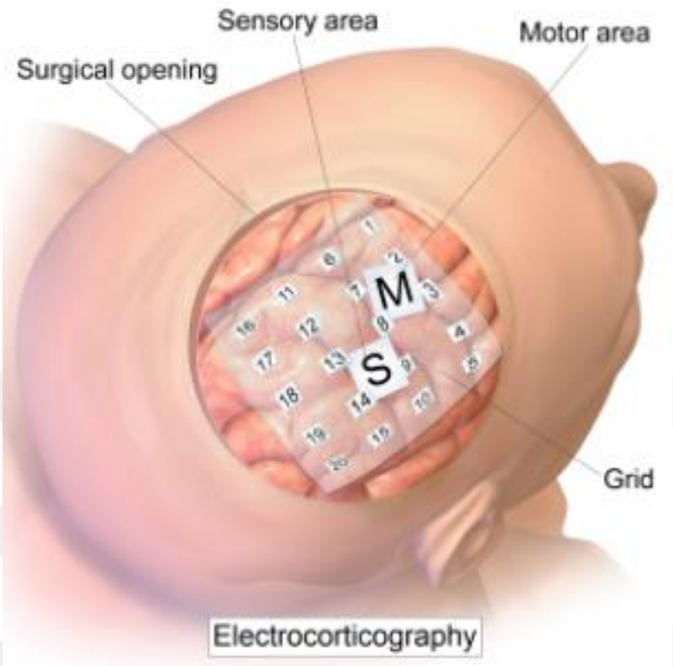

Figure 1.3: Partially Invasive BCI [8].

1.3.3. Non-Invasive BCI:

- It uses easily to connect.
- It has poor signals quality.
- It creates electromagnetic waves by the neurons.

In the non- invasive BCI system the electrodes are placed externally on the scalp and the signals produced from the brain activity can be recorded by these electrodes on the skull Algorithms then translate the bio-potential into instructions to direct the computer which will help people with brain injury to communicate with defined external devices without need to use the normal pathways such as speech or motion see Figure (1.4) and Figure (1.5) [9].

Figure 1.4: Non-Invasive BCI Electroencephalography (EEG) Electrodes Cap [8,9].

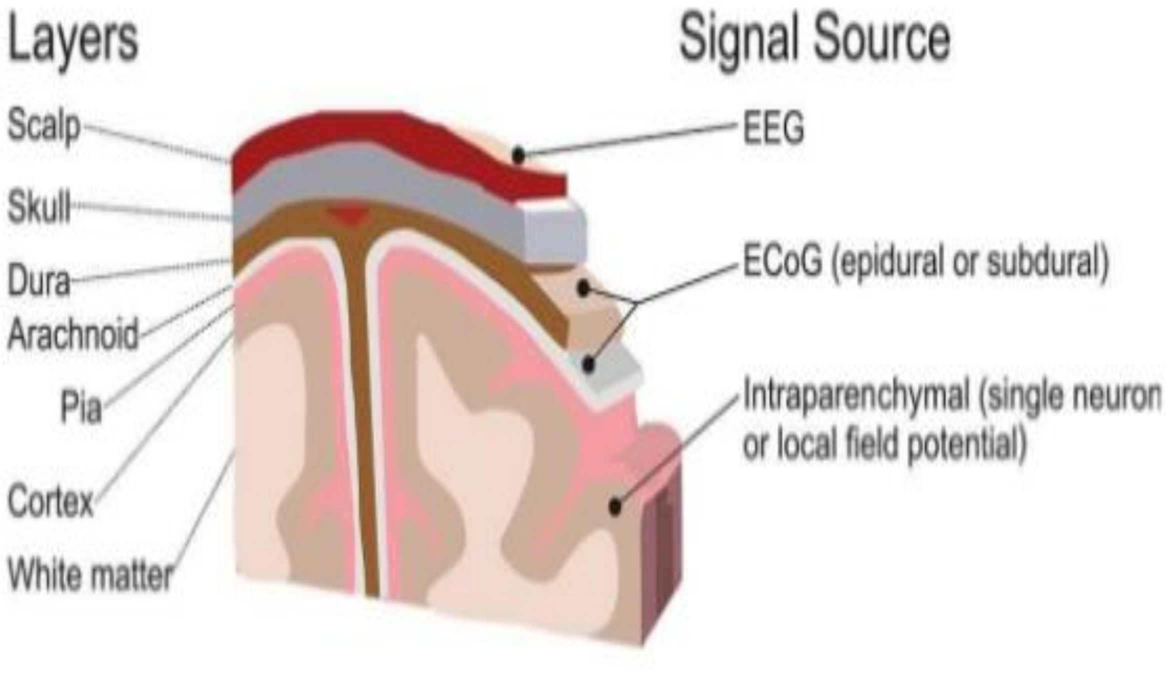

Figure 1.5: Brain Recording domains [8,9].

1.4. BCI Applications:

One of the most important applications that resulted from computer brain correlations is the ability to control the application of ideas across the brain. Perhaps the most important result of this is to exploit this feature for patients with motor functional problems. Through computer brain correlations, these patients will be able to communicate with their personal computer, move their wheelchair, or control their TV, music player or any home appliance that is used in everyday life efficiently and effectively [10].

The advantages of electrophysiological devices for the brain (for its ease of use and low cost) have made the applications of brain and computer interfaces more diverse and widespread. It is expected that the standard of lifetime of strictly inactivated persons are upgraded. Similarly, the eye paid by caregiver are less intense, and fewer costly, whereas creating the lives of relatives less nerve-wracking. In addition, applications of brain and computer interfaces are likely to be a controlling implement for highlighting information unseen in the operator's mind that he cannot express [11].

Applications of brain and computer interfaces serve mainly three groups. The first group includes patients with complete loss of mobility, possibly because they are in the final stages of endoscopic sclerosis or have severe cerebral palsy. The another collection includes almost paralyzed patients, but with the ability to move certain parts, like the movement of the eye, eye twinkling or lip movement. The collection three of users contains physically retarded persons. The brain and computer interfaces have petite to proposal for the set three, since they could guide the similar data faster and easier through other boundaries. However, brain and computer interfaces are increasingly used with physically retarded people in the areas of neural marketing and video-games like an implement to extract user data that cannot be expressed through traditional interfaces. Similarly, brain and computer interfaces could be useful for approximately persons with neurological disorders such as schizophrenia or unhappiness [12].

Applications of the brain and computer interface to communicate deal with severe communication disorders due to neurological disorders. This type of request may represent the maximum insistent investigation in the area of brain and computer interface, because communication is key to people. Communication applications the screen typically displays a virtual keyboard, with the user selecting a letter from the alphabet via the brain and computer interface [13].

Other important applications of computer interfaces and computers are Internet browsers that have been adapted to people with disabilities because Internet has become a very important part of everyday life over the last decade.

A person using the brain and computer interface to control an arm.

Spinal cord damage or other neurological disorders with harm of sensual and motorized purposes significantly reduce the lifetime class of the patient and cause lifelong dependence on homebased care facilities. Restoring movement may alleviate the patient's psychological and social. Program recovery (for example constipation of objects) is possible in patients with acute paralysis over artificial nerve limbs (such as a robot arm) guided by functional electrical stimulation [13].

Environmental control one of the majority aims of brain and mainframe interface applications is to maximize the patient's autonomy (in spite of any motor incapacity). Patients with severe motor incapacities are frequent two seats, which is why environmental control applications focus on controlling household appliances such as television, lights and temperature devices. Besides improving the quality of life of severely disabled patients, the tasks of caregivers will be less intense and costly, and the lives of their relatives will be less difficult.

A highly implemented example of environmental control is a mouse pointer that the user moves right, left, up, and down using the brain and computer interface (usually electrical brain planing devices), thereby controlling the operating system of the computer or any other home appliance [13].

Mobility applications of brain and computer interfaces that allow people with special needs to control transference characterize an essential area in their applications. Appreciations to these submissions, persons with paraplegia or another bodily disability can wheel independently, production them much independent and refining their feature of life [14].

A person with quadriplegia uses the brain and computer interface to control a virtual personality.

Applications of brain-based interfaces and entertainment-oriented computers have traditionally been less of a priority in this area. Research in the technology of brain and computer interfaces usually focuses on assistive applications for people with special needs (e.g., wheelchairs, wheelchair control, or artificial limbs) somewhat than entertainment applications. In recent years, Though, attention in entertainments application has increased due to significant technological advances. In fact, developments in the act of brain and computer interfaces have opened the way for wider use of people with disabilities. The brain and computer interfaces provided a new way of human-machine interaction that could make video games more challenging and attractive. In addition, the brain and computer interfaces provide a way to reach the user's impressions of the game's performance with him, thus improving the games through information about brain activity. Brain and computer interfaces can determine when a player is bored, anxious, or frustrated by using this information to design games in the future [14] [15].

Nervous marketing is a comparatively new area of investigation that smears neuroscience to advertising study. Neural selling might be a basis of much correct data about unclear user favorites, somewhat traditional marketing research information. Neurosurgery may reveal unseen data about real user partialities that couldn’t be expressed openly. The brain's reply to ads can be scaled, so the success of marketing movements can be measured.

Medicine, for a person's reactions when using the brain and computer interface the ability to induce cortical plasticity, this ability might be the source for many medicinal claims. Handlers can control certain discerning areas of the brain through nerve reactions, with the goal of making behavior vicissitudes in the mind. Neural responses providing by the brain and computer interface structure might advance mental act, language and emotion aids and pain management. They have also been used to treat mental disorders (e.g. Epilepsy, attention deficit disorder, schizophrenia, depression and alcoholism)). In another way, mind sign recordings can be used to measure brain function and assess their condition in health and disease [16].

2. LITERATURE REVIEW

2.1. What Are Brainwaves:

The human brain consists of billions of brain cells named by neurons. When communicating this neuron at the same time it generated a significant amount of electrical activity called brainwaves and measured in Hertz. The brainwaves are generally divided into five main frequencies: Beta waves, Alpha waves, Theta waves, Delta waves and Gamma waves. Not only brainwaves Different in frequency but also it was Different in amplitude.

Brainwaves are electrical waves of certain frequencies, which result from the work and activity of neurons in the brain, or "Neurons" Actually, brain waves are what represent our thoughts, feelings, feelings, and reactions [17].

Brainwaves are recorded based on a set of sensors placed on the head. The function of these sensors is to capture, record, process and display the electrical signals on the surface of the head. The process of capturing and recording signals can be done on the surface of the head, but it will be a difficult and complicated process due to the large interference that will be on the signals. The second way to record brainwaves is by placing the electrodes directly on the cerebral cortex according to the surgical procedure, and this method gives better and more accurate results. The process of recording and capturing brainwaves is known as EEG: Electroencephalography [18].

With regard to the details of the brainwaves themselves, they are divided into several bandwidths, each of which represents a particular pattern of mental activity. It is logical to note that high-frequency packets represent concentrated and intense mental activity (known as gamma waves) while low-frequency packets represent low mental activity, i.e., sleep situations (represented by the Delta Delta).

Speech means that brain waves will vary according to the mental activity of the person and according to the feelings he feels. When we feel tired and relaxed, lower-frequency brain waves are the dominant and most prevalent, while high-frequency brain waves occur when we are in high concentration and intense activity [19].

It is worth mentioning here that this article aims to highlight the concept of brain waves and types in general and comprehensive, while the careful and practical approach to the subject of brain waves and applications requires more complex details, especially that brain waves represent many things according to the region where the brain.

The frequency of the brainwaves is measured in Hertz or CPS: Cycle per Second. The following is the classification of the brain waves according to the frequency bands to which they belong [20].

2.1.1. Delta Waves:

It is the slowest brain waves in terms of propagation velocity. They are very low frequencies. These waves are generated in situations of deep mental activity, such as quiet meditation or deep sleep, and Delta waves are the source of empathy [21].

2.1.2. Theta Waves:

Most often, theta waves appear during sleep (not the deep sleep in which delta waves appear) and may sometimes appear in long and deep meditations. Theta waves are likened to our path and path to memories and information stored in the brain. Theta waves are responsible for drawing our senses from focusing on the surrounding medium, to focus on the signals generated within the brain. Theta waves are also responsible for dreams. Theta waves generate images, live scenes, information and knowledge that are not connected to the direct conscious perception we get from the senses of hearing, sight, smell, and others [22].

2.1.3. Alpha Waves:

Alpha waves represent the quiet state of the brain, which means that the brain is conscious and aware of what is around it, but it is inactive or active and can be likened to the "Stand by" state of the computer, Where the computer does not perform any action requires the capabilities of the processor, but the computer is ready to receive any signal or alert [23].

2.1.4. Beta Waves:

Beta waves appear dramatically when the brain is conscious and aware, and it also performs various functions and functions, all of which are related to the conscious perception of the senses. Beta waves represent the state of "activity" of the brain, and when they spread across the brain, it means that we do a variety of functions, such as thinking, problem-solving, looking and listening and receive various alerts. Beta waves are divided into three other bands:

- **Beta1:** low-bandwidth waves, which cover the bandwidth of 12-15 Hz, represent the lowest state of alertness and cognitive-brain awareness [24].
- **Beta2:** A band that covers a frequency band of 15 - 22 Hz, which represents a growing concentration of mental brain activity.
- **Beta3:** high waves: a band that covers a bandwidth of 22 - 39 Hz. These waves represent complex thoughts, learn new experiences, and stimulate brain states.

2.1.5. Gamma Waves:

Gamma waves are the fastest brain waves and highest in terms of frequency value. Gamma waves represent intense mental states, focused thinking, and also represent the response of several brain regions to contribute to a single focused thinking process. Previously, gamma waves are an additional brain activity that had no meaning; only research showed that they were actually the highest levels of brain activity. One of the puzzles about gamma waves is that it has a higher frequency than the frequency of signal transmission across the same neurons, and how the generation and emergence of gamma brain waves are still considered one of the important mysteries in the field of neuroscience [25].

2.2. Electrical brain signals:

The human brain consists of a group of cells known as neurons that communicate with each other in long neuronal axons. These neurons are in a working state every time we do something: move, think, feel, remember, etc. The neurons act as follows: When we want to do something, such as raising a glass of water to drink it, the neurons generate an electrical nerve signal, which moves through the axons to the nerve units, which are the muscles and bones, and the speed of transmission of these signals 400 km per hour. These electrical signals are generated mainly via electrophoresis difference in neuronal membranes [26].

Although the electrical nerve pathway is insulated, it is not perfectly insulated, so some electrical nerve signals can leak out. What neuroscientists and neuroscientists do is capture and record these signals to determine the effectiveness and nervous activity of nerve cells, thus determining the state of the brain as a whole. The opposite can also be done, namely, determining the response of neurons to the brain when a neurotransmitter is moved from a sensitive organ such as the eye. When the eye sees a specific color, a neurotransmitter is sent to the brain to explain. The neurons in the brain are the ones who will interpret it, so they will also produce electrical signals during their work. So, we can know exactly how the brain works and how it understands the world around us.

Now, how will we benefit from this information in a useful application? This leads us to the definition of the system of computer brain correlations and how it works [27].

2.3. BCI Inputs and Outputs:

So far, we have known that computer brain correlations are technique that relies on the electrical signals of the brain to control a device or an application, depending only on the person's own thoughts.

So, the first step (the most difficult step) would be to secure an effective threading interface, recording these signals, and converting them to useful data that contributes to controlling the desired application and according to the person's own thoughts. This is known as the "Interface Mechanic" mechanism [28].

The simplest mechanism of correlation is to rely on the electrical brain diagram EEG, as a non-surgical way to register the electrical activity of the brain, where the placement of external measuring electrodes on the surface of the head, which is the process of sensing the electrical signals resulting from the work of neurons and then form a signal proportional to electricity - The electrodes are induced by the electrical signals of the brain - then the signal is amplified and filtered and the noise associated with it is eliminated (the electrical signals of the brain are microfluet). These signals are then sent to be recorded in a computer system Specialization. This method does not have the accuracy required and sufficient to provide a strong and effective signal can be invested to control a device [29].

The second method that can be used as a threading mechanism is to place the measurement electrodes directly into the gray matter of the patient, through a simple surgical procedure. This method provides greater accuracy in the capture and recording of electrical signals, and also provides higher accuracy in terms of the quality of recorded signal; The electrodes can be placed in the specific brain region to be recorded, such as conscious thinking, memory, sensation, and so on. The problem of this method is that it requires surgical work, and the electrodes deposited in the brain will cause scar tissue to be planted, and these scars will later affect the quality of the signal extracted [30].

Regardless of where and how the electrodes are placed (whether external on the surface of the head or internal on the gray material), the mechanism of action is one: the electrodes record the electrical activity of the neurons, then amplify the signal, then filter it and get rid of the accompanying noise, and then interpret it through the program my computer is specialized. In reversible systems, the opposite is done: A computer system generates the appropriate and sufficient voltage to alert the neurons and send the signal to them.

There are also other ways to measure brain activity using magnetic resonance imaging (MRI). Magnetic Resonance Imaging (MRI) devices perform high-resolution imaging and visualization of brain activity but cannot be used as part of a computer brain-binding system because of their large size, complex structure, and high noise.

As a conclusion to our poverty, we can say that the income of the computer brain correlative system is the electrical signal of the brain that is interpreted by a specialized computer system, and its graduation is appropriate to control a given application [31].

2.4. Electroencephalography (EEG):

German psychologist Hans Berger in 1924 first was recorded electric activities in peoples by placing electrodes on the scalp and the galvanometer. In 1929, in spite of primitive instruments and strategies by that time, he was capable to define some low frequency vibrations called alpha waves. Following these parameters, the basic ideologies and processes for (EEG) planning have hardly transformed.

Electroencephalography (EEG) signals recording from the surface of the scalp are the best signals uses to brain computer interface, because this method of signals the brain activity is easy to use and very inexpensive. The electrical brain activity is represented by electroencephalogram (EEG) signals. The best way to get EEG signals from surface of the scalp is use the electrode scheme as shown in Figure (2.1) [31].

(EEG) is naturally a non-intrusive method (though, usually used as electrodes in special applications) to record the electric activities of the mind sideways the scalp. The brainwave chart actions fluctuation in the voltage generated by ionic currents in brain neurons [31]. This technique is referred to in the clinical field as a recording of the automatic electric activities of the mind done a dated of period [31]. It is measured by several electrodes located on the scalp. Diagnostic uses usually effort on the spectral contented of brainwave planning to appear in signs of EEG. Brain planning is used extensively to analyze epilepsy, which grounds abnormal patterns in EEG reading [32]. This mechanism is as well using to analyze slumber sicknesses, coma, cerebral anomalies, and mind decease. EEG was used as a primary diagnostic technique for tumors, hit and extra principal mind sicknesses [33]. However, its use may decrease with the advent of high resolution anatomical imaging techniques, such as magnetic resonance imaging (MRI) and computed tomography (CT). Regardless of limited spatial precision, brain planning remains a valuable tool in the fields of research and diagnostics, particularly when a temporal resolution of a fraction of thousandths of a second is required, which is not provided by other methods like attractive character imagine and tomography. One of the brainwave-derived derivatives is called the excited effort (EP), which involves the equation of brainwave planning activity to be time-bound with exposure to a given stimulus (optical, tactile, or audit stimulus). Efforts associated with the ERP event refer to the modified brainwave planning replies that are time-bound for much multifaceted processes of stimuli; This method is using in the mental skills, mental psychology study [34].

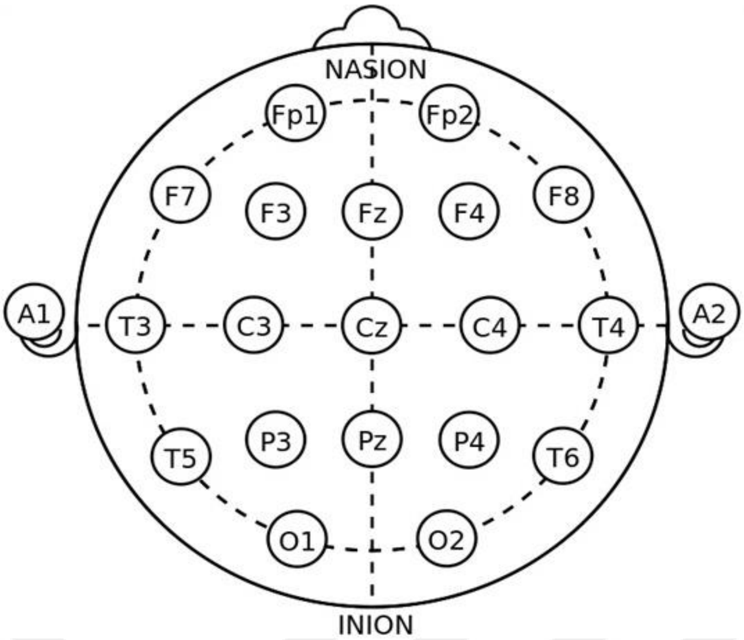

Figure2.1: EEG electrode placement schemes [35].

The human brain waves have four main frequencies are, see Figure (2.2):

- **Delta:** It is frequency ranges from 1 Hz to 4 Hz. It is known as high in amplitude and the slow wave.
- **Theta:** It is frequency range between 4Hz and 8Hz. It is known as "slow" activity.
- **Alpha:** It is frequency range between 8 Hz and 12 Hz. It is higher in amplitude.
- **Beta:** It is frequency range between 12 Hz and 40 Hz. It is classified as "fast" activity. These are known as high frequency low amplitude brain waves.

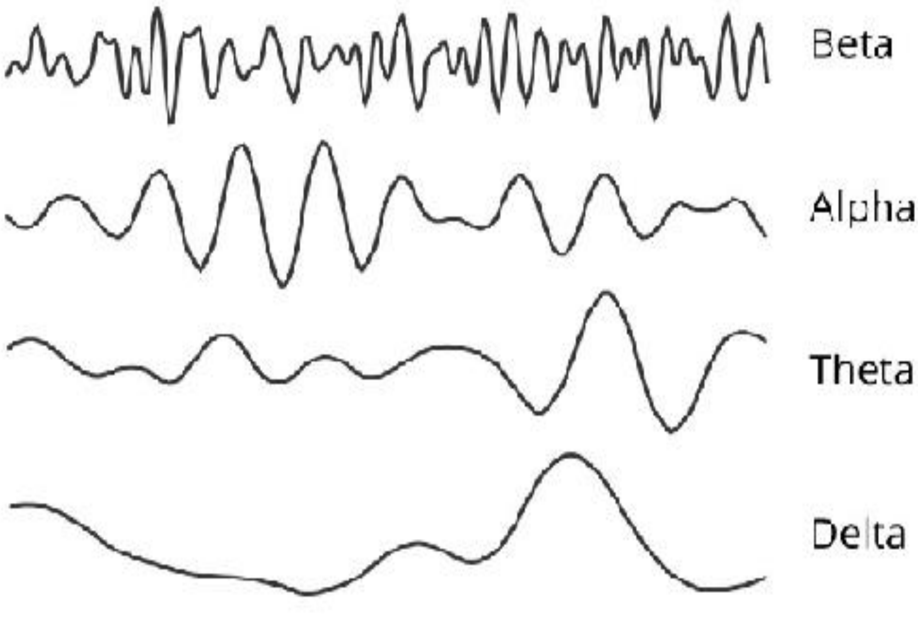

Figure 2.2: Brain wave samples to beta, alpha, theta, and delta.

2.5. Signal Processing Technique:

For BCI design, the EEG signals processing is meant to translate EEG raw signals into a category of those signals, that is, to the calculable psychological state of the user. This translation is typically achieved by employing a pattern recognition approach, that consists of two main steps:

- **Extraction:** In signals processing steps the feature extraction method has important role to extracting features from signals. also, in this step the extracted features from signals should be convert in to some values, and this value ready and easy for classification steps.
- **Classification:** This step is named by classification; the classification step uses to classify important features are extracted from signals.

For example, let's consider BCI, supported Motor imagery (MI), i.e., BCI that may acknowledge imaginary movements appreciate the left or right hand movements. during this case, the two mental states known are the movement of the left on one facet and therefore the mental image of the right hand movement on the opposite. to spot them from electroencephalogram signals, typical features are power-range features, i.e. the strength of an electroencephalogram signal in an exceedingly given frequency vary. For the UL order, the strengths of the band are usually extracted in μ (between 8-12 Hz) and β (between 16-24 Hz) frequency bands, for the conductor localized on the pallium regions (around C3 and C4 locations for left and right-hand movements tively) (Pfurtscheller and Neuper, 2001). These features are then categorized by exploitation Linear Distinguish Analysis (LDA) [36].

There are many steps for analyzing EEG signals such as pre-processing like the remove of noises such as the baseline noise, power line interference and eye blink pollution, feature extraction method uses to extract representative values of the signals through modeling techniques, feature selection step which select important feature to analyze, feature classification step uses the extracted features are classified in specific for the main application, for example controlling some devices such as computers and robots. There are many methods for signals processing such as Fourier Transform (FT) and Wavelet Transform (WT) Method. To extract feature and classification from EEG signal a professional way is feature extraction method see Figure (2.3) [37].

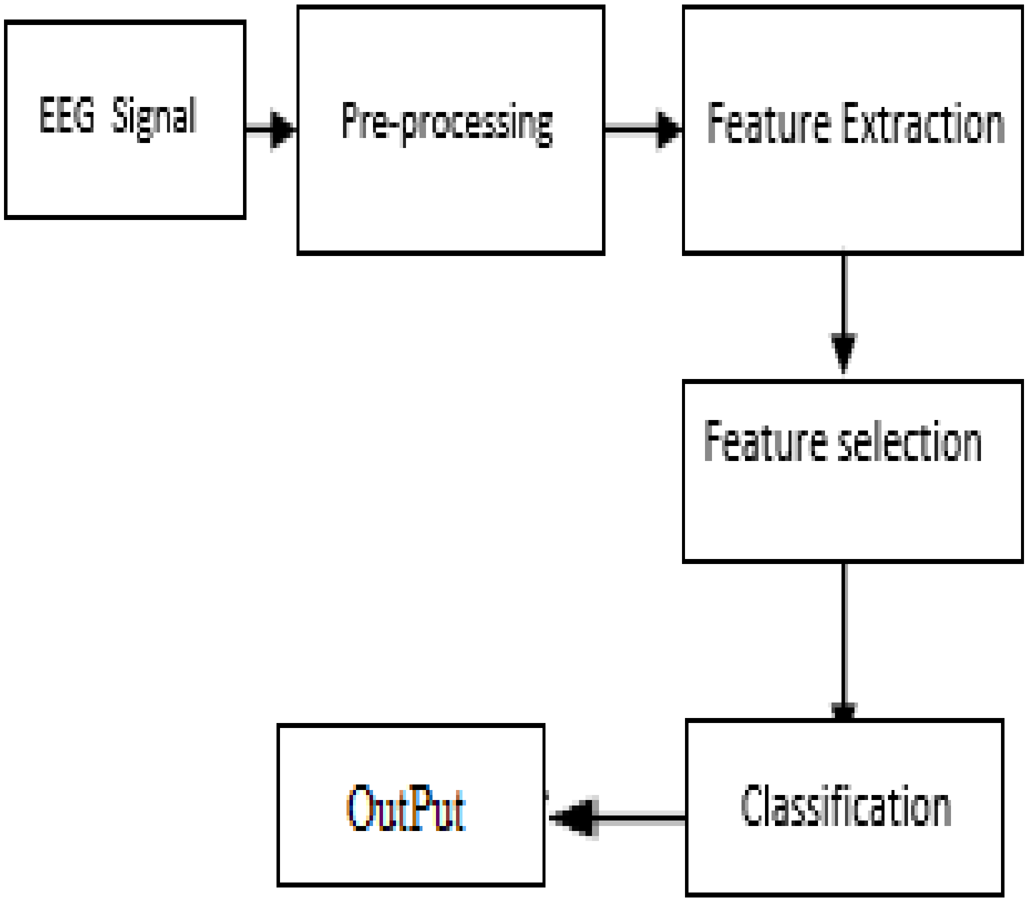

Figure 2.3: The basic steps for EEG signals processing.

2.6. Features Extraction:

In recent years, feature extraction technique has important role in signal processing, there are many feature extraction methods to extracting features from EEG signals such as Fourier Transform, Short-Time Fourier Transform and The Wavelet Transform. This step is used to convert original brain wave to some values, important investigations in this step we can classified those values easily by using classification methods and then convert to commands by using machine learning as shown in Figure (2.4). We can extract features from EEG signals by using two various domains like Time and Frequency domain features (TDF) (FDF) [38].

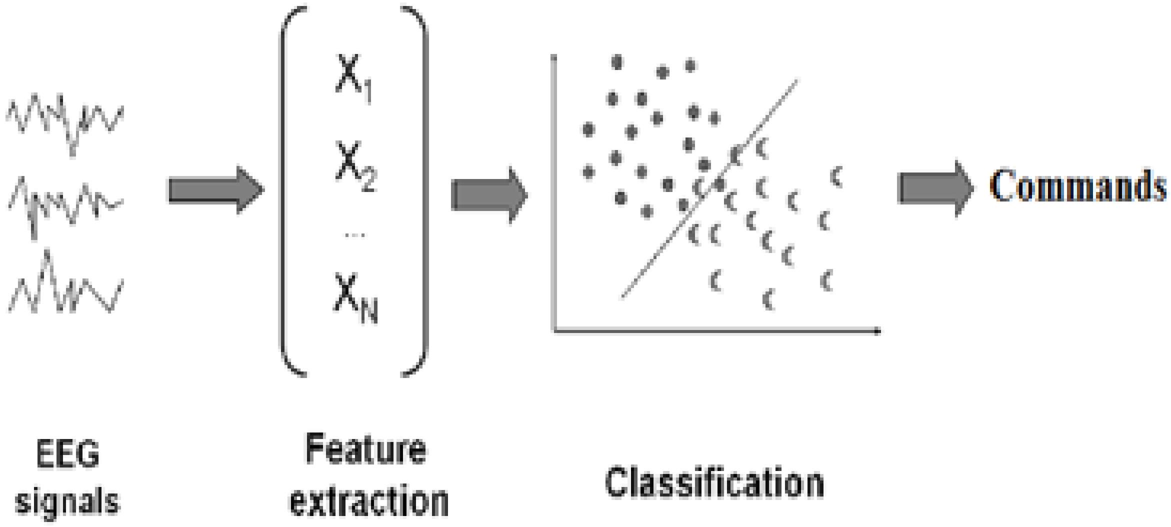

Figure 2.4: The steps for EEG signals processing.

The way of work, the interface of the brain and computer aims to identify certain patterns in the brain signals, and this process is done through several consecutive steps:

- **Signal recording:** recording of brain signals, with the possibility of reducing noise and addressing signal recording defects.
- **Pre-treatment:** Signal processing is appropriate for subsequent processing (sometimes incorporated in the previous step).
- **Extraction of traits:** In which brain signals are converted to a matrix containing important attribute data.

The classification of brain signals (depending on the matrix of important qualities) and the translation of what the user thinks.

Application interface: The result of the classification is converted to understandable commands for the connected devices.

3. FEATURES EXTRACTION METHODS

The unique brainwaves have a noise and we cannot use this wave for brain-computer interface easily. there are many steps for EEG signal processing. the most important steps use for brain-computer interface systems are feature extraction technique. This technique has the best role in extracting a feature from signals and converts to some values. There are many methods for extracting a feature from EEG signals and each one has advantages and disadvantages [39].

The original EEG signal is that the time domain signals and also the signals power distribution square measure distributed. In order to extract features, the EEG signals is analyzed to allow a signals power description as a function of time or frequency. Based on previous studies, the characteristics of the extractor within the frequency domain are one of the most effective to spot mental tasks supported EEG signals analyses [40].

Technically, the property represents a characteristic property, a place able measure, and a practical element obtained from a part of the pattern. The extracted features aim to scale back the loss of important data contained in the signal. additionally, it also simplifies the number of resources required to accurately describe a wide range of knowledge. this is often necessary to scale back the complexness of implementation, to scale back the value of process info, and to eliminate the potential would like for info compression. Recently, a large form of strategies are accustomed extract options from graph signals. These embody time-frequency distribution (TFD), fast Fourier transform (FFT), eigenvector (EM), wavelet Transform (WT) Automatic reduction methodology (ARM), and so on. In general, graph analysis has been the topic of many studies, given its ability to supply associate objective methodology of recording brain stimulation that's wide utilized in pc interface analysis within the brain with application in diagnosing and rehabilitation engineering. Therefore, the needs of this paper can discuss some ancient strategies of extracting the graph feature, examination its performance to a particular task, and at last, recommending the foremost acceptable thanks to extract the performance-based advantage [41].

EEG is one of the areas in the diagnosis of epilepsy. The EEG records can provide a valuable look and better understanding of the mechanisms that cause epileptic disorders. the Fourier transform (FFT) and wavelet conversion are used as spectral analysis tools for EEG signals. These methods can provide a time-varying frequency of EEG signals. Since frequency characteristics are important observable information from signals, FFT and wavelet conversion are among the best ways to analyze EEG signals. Comparisons are also made between these two methods. The result showed that wavelet conversion was better than FFT in the analysis of EEG signals.

3.1. Fast Fourier Transform (FFT) Method:

(FFT) is an algorithm can use for signal processing and signals feature extraction. this technique services some accurate incomes or tools or equations for analyzing EEG information. this method utilizes to change signals from time-domain to frequency-domain and vice versa. Features of the obtained EEG signal to be examined are calculated by power spectral density (PSD) estimation so as to by selection characterize the EEG models signal. But, four frequency bands cover the main characteristic waveforms of EEG spectrum [42,43,44].

The PSD is examined by Fourier transforming the evaluated autocorrelation arrangement which is initiate by nonparametric approaches. The Welch's method is One of these methods. The data sequence is utilized to data windowing, the result modified periodograms. The information sequence xi(n) be represented as

$$\boldsymbol{x_i(n) = x(n + iD), \qquad n = 0, 1, 2, \ldots, M - 1} \tag{3.1}$$

$$\boldsymbol{while\ i = 0, 1, 2, \ldots, L - 1;}$$

iD takes to be first point of start of sequence ith and then L takes for length of 2M perform information’s segments that are created, the outputs results give.

$$\boldsymbol{P_{xx}^{\approx(i)}(f) = \frac{1}{MU}\left|\sum_{n=0}^{M-1} x_i(n)w(n)e^{-j2\pi fn}\right|^2} \tag{3.2}$$

In this function, named by window function, U bounces regularization feature of the power and is chosen like that.

$$\boldsymbol{U = \frac{1}{M}\sum_{n=0}^{M-1} w^2(n)} \tag{3.3}$$

Where w(n) is the window function, the average of these modified periodograms gives Welch's power spectral as follows:

$$\boldsymbol{P_{xx}^{W} = \frac{1}{L}\sum_{i=0}^{L-1} P_{xx}^{\approx(i)}(f)} \qquad (3.4)$$

3.2. Wavelet Transform (WT) Method:

P.Jahankhani and K.Revett have proposed Wavelet Transform (WT) to analyze various transient events in the field of biomedicine. They have described that WT is fit for non-fixed signals and has more benefit than spectral investigation. For timing, signal wave representations are an actual technique. The significant feature of WT is that they provide exact frequency data at low frequencies and exact period data on high frequencies. This belonging is significant in biomedical claims. Because most references in the biomedical area continuously cover high-frequency mechanisms with short period and low-frequency mechanisms with a long-time period. WT offers multiresolution examination of nonstationary signals [45].

This method is a period frequency investigation; Wavelet analysis method defines an algorithm which involves the multistage window method. In this method the length of window has variable size this feature of wavelet is used in this technique. This method involves the use of large time interval where we need low frequency data and where we have to find high frequency data we need to set the length of window to be shorter so accordingly we can use this type of technique. Fourier transform cannot be useful to the transitory signals as plenty of signals in EEG contains non-stationary components so this technique cannot be applied for EEG so wavelet transform must be used in wavelet transform variety of probing function are used and depending upon the comparison with the threshold function window length can be control and we can easily extract features from the signals. This concept leads to the function for the continuous wavelet transform (CWT) [46].

$$\boldsymbol{CWT(a,b) = \int_{-\infty}^{\infty} x(t)\psi_{a,b}^{*}(t)dt} \qquad (3.5)$$

One major advantage of wavelet technique is its flexibility to perform general analysis that is, to analyze or can be apply to localize the window size and localization area of a larger signal is done. In the wavelet packet technique, signal is compressed and noise is removed by using the Fourier transform technique exactly same ideas can be developed to extract the feature of EEG signal the basic idea and technique will be the same as traditional method but the only difference is that we can easily analysis the complex problem in easy and flexible manner and here we have to deal with EEG signal as in wavelet analysis approximations method are used to spilt the details of signals as shown below and these details will be the required feature. The mined wavelet coefficients afford a compressed symbol that displays the energy distribution of the EEG signal in time and frequency. The subsequent numerical structures could be used to characterize the time–frequency distribution of the EEG signals such as mean of the complete standards of the coefficients, the power average of the wavelet coefficients in each sub-band and he subsequent numerical structures were used to characterize the time frequency distribution of EEG signals which are mean of the absolute of coefficients in each sub bands and Average power of wavelet coefficients in each sub band. These structures characterize the frequency distribution of signal. The coefficients Standard deviation in each sub bands and ratio of absolute mean values of adjacent sub bands represents the amount of changes in frequency distribution so these features were considered for the specific application and used for the classification of EEG signals [47].

3.2.1. Continuous Wavelet Transform (CWT) Method:

This can be expressed as

$$\boldsymbol{CWT(a,b) = \int_{-\infty}^{\infty} x(t)\psi_{a,b}^{*}(t)dt} \tag{3.6}$$

$x(t)$ standing for the unprocessed EEG, where a standing for dilation, and b representing translating feature. The $\Psi a, b(t)$ denotes the complex conjugate and can be calculated by

$$\boldsymbol{\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\psi\left(\frac{t-b}{a}\right)} \tag{3.7}$$

where $\Psi(t)$ means wavelet. Though, its main weaknesses is that evaluating parameters a and translation parameters b of CWT change continuously. Thus, the coefficients of the wavelet for all accessible gages after calculating will consume many of energy and crop many of amusing data [48].

3.2.2. Discrete Wavelet Transform (DWT):

In demand to report the softness of the CWT, discrete wavelet transform (DWT) had stayed cleared on the base of multiscale feature image. All the gage below consideration characterizes an exclusive thickness of the EEG signal. The multiresolution decomposition of the raw EEG data $x(n)$ is showed in figure (3.1). Every stage covers two digital filters,

$g(n)$ and $h(n)$, also two down samplers by 2. The discrete mother wavelet $g(n)$ is a high pass in nature, while its mirror image is $h(n)$ is a low-pass in nature.

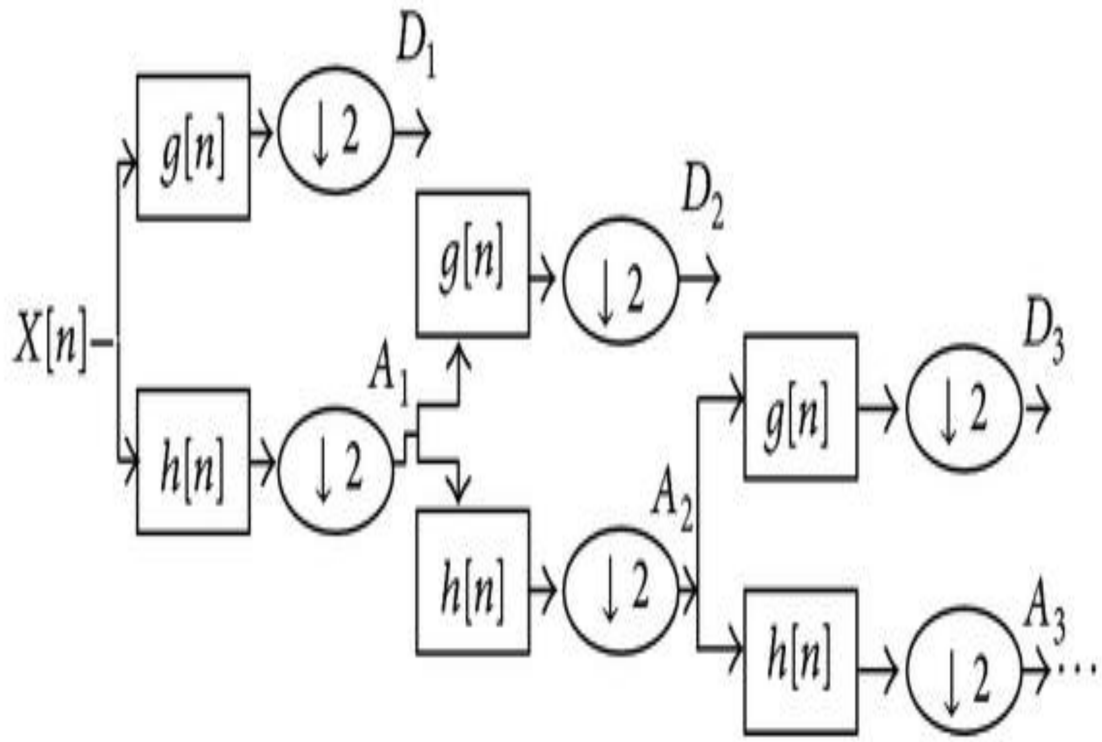

Figure 3.1: Implementation of decomposition of DWT.

As in the Figure (3.1) shown, every step output offers a details of the signal *D* and an estimation of the signal *A*, where the latest changes an input for the following stage. The number of stages to which the wavelet decomposes is selected dependent on the element of the EEG data with dominant frequency [49].

The connection among WTs and filter *h*, that is, low pass, could be characterized as following function:

$$\boldsymbol{H(z)H(z^{-1}) + H(-z)H(-z^{-1}) = 1} \qquad (\mathbf{3.8})$$

Here, H(z) represents filter's h z-transform. The high-pass filter's complementary z-transform is expressing as

$$\boldsymbol{G(z) = zH(-z^{-1})} \qquad (\mathbf{3.9})$$

By accurately describing the signal segment characteristics within a specific frequency domain and localized domain characteristics, there are many advantages that go beyond the high computing and memory requirements of traditional convolution-based DWT implementation.

3.3. Eigenvectors:

There are three algorithms based on Eigenvectors method such as Pisarenko method, MUSIC method, and minimum method. These methods are used to calculate signal frequency and strength of measurements controlled by artifacts. The substance of these methods is the ability to decompose Eigen to link out the signals off the tool [50].

3.3.1. Pisarenkos Method:

Pisarenkos method is one of those methods among the obtainable eigenvector access to use for evaluating power spectral density (PSD). The accurate countenance A(f) is employed to calculate the PSD [51].

$$\boldsymbol{A(f)} = \sum_{\boldsymbol{k=0}}^{\boldsymbol{m}} \boldsymbol{a_k e^{-j2\pi fk}} \qquad (\boldsymbol{3.10})$$

In above equation, $a\ k$ stands for coefficients of the defined equation and m defines eigenfilter's $A(f)$ order. The Pisarenko method uses the objective-signal equation to estimate the PSD of the eigenvector signal similar to the minimum eigenvalue, as follows:

$$\boldsymbol{P_{PISARENKO}} = \frac{\boldsymbol{1}}{|\boldsymbol{A(f)}|^2} \qquad (\boldsymbol{3.11})$$

3.3.2. MUSIC Method:

This technique eliminates problems connected to faulty zeros with the help of the average equivalent spectra of the partial space of the complete parts of the waste. Thus the spectral density of the resulting power is obtained as

$$\boldsymbol{P_{MUSIC}(f)} = \frac{\boldsymbol{1}}{(\boldsymbol{1/K}) \sum_{\boldsymbol{i=0}}^{\boldsymbol{K-1}} |\boldsymbol{A(f)}|^2} \qquad (\boldsymbol{3.12})$$

3.3.3. Minimum Norm Method:

In this technique types the zeros wrong in the unit ring to separate them from the actual zeros to be able to analyze the partial space vector noise required of a sub-wave noise or noise signal. However, while Pisarenko's technique is a model of the sub-space of noise that corresponds to the minimum intrinsic value, the minimum of the base technique selects a linear grouping of all the sub-factors of the noise sub-areas [52]. This technique is described by

$$\boldsymbol{P_{MIN}(f, K)} = \frac{\boldsymbol{1}}{|\boldsymbol{A(f)}|^2} \qquad (\boldsymbol{3.13})$$

All of the above eigenvector methods can better handle the signal which consists of many distinct sinuses involved in the noise. Thus, they are prone to give false zeros, and thus lead to relatively poor statistical precision.

3.4. Time Frequency Distributions:

These approaches need noises to afford perfect execution. Consequently, the very restricted pretreatment phase is needful for the disposal of all types of artifacts. Because they are time frequency approaches, they contract with a fixed belief; therefore, the process of windows is required in the pre-processor. The TFD of x (n) is defined by Cohen as [53].

$$\boldsymbol{P(t,w) = \frac{1}{2\pi}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} A(\theta,T)\Phi(\theta,T)e^{-j\theta t - jwt}d\theta dT} \qquad (\mathbf{3.14})$$

Where

$$\boldsymbol{A(\theta,T) = \frac{1}{2\pi}\int_{-\infty}^{\infty} x\left(u+\frac{T}{2}\right)x^{*}\left(u-\frac{T}{2}\right)e^{j\theta u}du} \qquad (\mathbf{3.15})$$

$A(\theta,\tau)$ is identified as opacity function, and $\Phi(\theta,\tau)$ recommend to kernel of the distribution, while rand w are time and frequency dummy variables, correspondingly.

Smooth pseudo-Wigner-Ville (SPWV) distribution is a different procedure which includes smoothing by freelance windows in time and frequency, namely, $W\ w(\tau)$ and $W\ t(t)$ [54]:

$$\boldsymbol{SPWV(t,w) = \int_{-\infty}^{\infty} W_w(T)\left[\int_{-\infty}^{\infty} W_t\,(u-t)x\left(u+\frac{T}{2}\right)\times x^{*}\left(u-\frac{T}{2}\right)du\right]e^{-jwT}dT} \qquad (\mathbf{3.16})$$

The feature extraction method is based on the frequency, energy and length of the main route. Each segment specifies the values E k, F k and L k. The EEG signal is first divided into k segments; then a vector of three-dimensional characteristics will be constructed for each segment. The energy of each segment k can be calculated as follows:

$$\boldsymbol{E_k = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} \vartheta_k(t,f)\,dt\,df} \qquad (\mathbf{3.17})$$

where $\vartheta_k(t, f)$ represents the representation of time frequency of the segment. However, to calculate the frequency of each segment k, we use the cutoff frequency as follows:

$$\boldsymbol{F_k = \int_{-\infty}^{\infty} \vartheta_k(t, f)\, dt} \qquad (\mathbf{3.18})$$

Lastly for obtain best outcomes, must uses EEG signals without noise or a good signal should be used for TFD.

3.5. Autoregressive Method:

Zabede and W.Mansor, proposed the Autoregressive Model (AR) as a method of extracting the feature to classify the writing task of the EEG signal. advanced writing provides useful information that is used to improve typing errors. They used an AR model with multilayer perceptron (MLP) to distinguish the alphabets. The AR model is used to apply the characterization of the EEG signal. It is also used to detect mental tasks using the neural network and provides 91% accuracy. The EEG signal undergoes changes in capacitance as well as frequency while different mental tasks are performed. Hence these features can be captured and extracted using modeling techniques, such as autoregressive models. The AR model was widely used for EEG analysis. It shows the linear composition of ICA and past EEG which brings present EEG samples. The basic idea of the autoregressive model (AR) is the assumption that the real EEG can be approaching the so-called AR process. With this assumption, the system and the AR approximation parameters are chosen in a manner that best fits the EEG measurement. For each AR model, this provides an alternative method for EEG spectral properties.

Autoregressive methods (AR) estimate the power spectral density (PSD) in an EEG using a standard scale. Therefore, AR methods do not experience the problem of spectral leakage and therefore result in better frequency accuracy than the non-amalgam approach. The estimate of PSD is achieved through the transaction account, i.e. the parameters of the linear system under consideration. There are two methods used to estimate AR models outlined below [54,55].

3.5.1. Yule-Walker Method:

The mass of the Yule-Walker method is estimated by the spectral density of the PSD for input using the Yule-Walker AR method. This method, also called a self-bonding method, fits auteggressive (p) model for the input data window. It does this by reducing the forward prediction error in the sense of the least squares. This formula leads to the Yule-Walker equation, which was solved by the lute- Levinson-Durbin. Block outputs are always illogical.

The input must be a column vector. This entry represents a frame for consecutive time samples of a single channel signal. The cluster outputs a column vector that contains the power spectral density estimate of the signal at the evenly spaced N_{fft}. The frequency points are in the range [0, F_s], where F_s is the sampling frequency of the signal.

When you specify a request for an inheritance estimate from the input dimensions, the entire column model order is less than the size of the input frame. Otherwise, the value of the Order parameter determines the order. To ensure valid output, a parameter must be an order of magnitude less than or equal to half the length of the input vector. The spectrum mass of FFT is calculated for estimated AR model parameters [56].

Determining the duration of the FFT inheritance from the Grading Order parameter determines that Fft is greater than the order of the estimate. The FFT Inheritance Length check box allows you to use the FFT length parameter to specify N_{fft} as a power for 2. Pads zero or wrap input to N_{fft} before FFT calculation.

When you select the When inheriting a sample from input check box, the block calculates the frequency data from the input signal sample period. In order for the cluster to perform a valid production, the following conditions must contain:

- The entry to the block is the original signal, but no samples are added or deleted (for example, by entering zeros).
- The duration of the time domain sample in the simulation is equal to the sample period of the original time series.

If these conditions do not persist, clear the When the sample is inherited from input check box. You can then specify a sample time by using the sample time for the original time series parameter.

See the Burg Method Block Reference to compare the Burg method, the contrast method, the modified variance method, and the Yule-Walker blocks of the Estimator AR. The Yule-Walker AR and Burg Method parameters return results that are similar to the lengths of the large buffer.

In this method, AR parameters or coefficients are estimated using the biased approximation resulting from the self-data function. This is done by finding the minimum of the lower squares of the forward prediction error as shown below:

$$\begin{bmatrix} r(0)_{xx} & r(-1)_{xx} & \cdots & r(-p+1)_{xx} \\ r(1)_{xx} & r(0)_{xx} & \cdots & r(-p+2)_{xx} \\ \vdots & \vdots & \ddots & \vdots \\ r(p-1)_{xx} & r(p-2)_{xx} & \cdots & r(0)_{xx} \end{bmatrix} \times \begin{bmatrix} a(1) \\ a(1) \\ \vdots \\ a(p) \end{bmatrix} \qquad (\mathbf{3.19})$$

where r_{xx} can be defined by

$$\boldsymbol{r_{xx}(m) = \frac{1}{N}\sum_{N=0}^{N-m-1} x^*(n)x(n+m), \quad m \geq 0} \qquad (\mathbf{3.20})$$

Calculating the above set of (p + 1) linear equations, the AR coefficients can be obtained as follows:

$$\boldsymbol{P_{xx}^{BU}(f) = \frac{\sigma_{wp}^2}{\left|1 + \sum_{k=1}^{P} \widehat{a}_p(k) e^{-j2\pi fk}\right|^2}} \qquad (\mathbf{3.21})$$

while $\sigma\hat{}wp$ gives the approximated lowest mean square error of the pth-order predictor given as follows:

$$\boldsymbol{\sigma_{wp}^2 = E_P^f = r_{xx}(0)\prod_{k=1}^{p}[1 - |a_k(k)|^2]} \qquad (\mathbf{3.22})$$

3.5.2. Burg's Method:

An AR spectrometric estimate based on the reduction of forward and backward prediction errors to satisfy the Levinson-Durbin recursion oud. The Burg's method estimates the reflection coefficient directly without having to calculate the self-bonding function. This method is characterized by the following force: The Burg method can estimate PSD data records to look exactly like the value of the original data. Sinus coated in signals can be produced as soon as they contain a low level of noise [57].

The difference between the Yule-Walker and Burg's method is in the PSD calculation method. For the Burg method, PSD is estimated as follows:

$$\boldsymbol{P_{xx}^{BU}(f) = \frac{\widehat{E}_p}{\left|1 + \sum_{k=1}^{P} \widehat{a}_p(k) e^{-j2\pi fk}\right|^2}} \qquad (\mathbf{3.23})$$

Parametric methods such as autoregressive one reduces spectral leakage problems and produce better frequency accuracy. However, choosing the right order is a very serious problem. Once the demand is too high, the output will trigger wrong peaks in the spectra. If the demand is too low, the result will be smooth [58].

4. PERFORMANCE OF METHODS

The main goal of this thesis is to review the steps used to BCI technique based on EEG signals. we explained five methods has the different performance to extracting the feature from electroencephalography EEG signals such as Fast Fourier transform (FFT), wavelet transform (WT), and AR. The feature extraction methods are one of the significant steps to signal analyses, each one of this methods have a different way to solve. In this step should be careful to choose one method of extracting information without losing any important data. Each one of this methods has some advantages and disadvantages or weakness point based on speed and accuracy of analyzing and extracting features or information’s from EEG signals.

It includes representation by waves, which is a set of functions derived from diseased waves through expansion and translation. Variable size window is the most important specification of this method because it ensures appropriate frequency accuracy in all frequency bands. Self-regression analysis suffers from speed and does not always apply in real time analysis, while the FFT seems to be the least discussed because it is unable to examine non fixed signals. The strength of the AR method can be confirmed by an additional comparison of its performance with the classical FFT as shown in Table (4.1).

Table 4.1: Comparison between FFT, WT and AR.

Methods	**Frequncy Resolution**	**Spectral leakage**
-FFT-	-Low Frequncy-	-High Spectral-
-WT-	-High Frequncy-	-Low Spectral-
-AR-	-High Frequncy-	-Low Spectral-

The AR method it's powerfully suggested be utilized in conjunction with additional conservative methods, such as graphs, to assist select the right order of the model and avoid phishing with pseudo spectral features [58].

The most vital application of electronic fields is the assessment of the frequencies and powers of signals from a noise canceling signal the principle of this method is to decompose the correlation matrix of the damaged noise. three methods were mentioned for the eigenvectors: Pisarenko, Multi Signal Classification and Minimum Standards. The great factor regarding the eigenvector technique is that it produces high frequency spectra even once the signal to noise quantitative relation (SNR) is low. However, this method may result in false zeros leading to poor statistical accuracy.

The TFD method provides the ability to analyze long-term segments of EEG data even when signal dynamics change rapidly. At the same time, it is necessary to have a good resolution at the time and frequency, making this method not preferred for use in many cases.

The Fast Fourier Transform (FFT) uses for narrowband stationary signals the analysis methods are frequency domain. This method has some advantages and also have some disadvantages. The advantages of this method are:

- For stationary signal processing have a best tool.
- For the sine waves it has more suitable for narrowband signal.
- Its speed is enhanced on all other methods available in real time.

The disadvantages of this method are:

- it has weakness in the analysis of non-stationary signals such as EEG signals.
- It does not have a good spectral estimate and cannot be used to analyze short EEG signals.
- FFT cannot detect local protrusions and complexes that are typical of epileptic seizures in EEG signals.
- FFT suffers from a high sensitivity to noise and has no shorter data record duration.

Wavelet transform(WT) method is suitable for transient and stationary signal and the Analysis Method is Both time and frequency domain, and linear, and the advantages of this method are:

- have a varying window size, wide band at low frequencies and narrow at high frequencies.
- is more suitable for analyzing sudden and transient radiological changes.
- It is preferable to analyze irregular data patterns, such as impulses in different time situations.

The disadvantages of this method are:

- Needs selecting an appropriate wavelet.

Eigenvector method is suitable for signal buried with noise and the analysis method is Frequency domain, and the advantages of this method are:

- Provides appropriate accuracy for assessing sinus data.

The disadvantages of this method are:

- The lowest intrinsic value may generate false zeros when using the Pisarenko method.

The Time frequency distribution method is suitable for stationary signal and the analysis method is both time and frequency domains, and the advantages of this method are:

- It gives the feasibility of examining large continuous slices of the EEG signal.
- TFD only can analysis clean signals for perfect result.

The disadvantages of this method are:

- Time-frequency methods are addressed to deal with the concept of stationery; as a result, the process of windows in the pre-treatment unit is required.
- Too slow (due to incremental gradient calculation).
- The extracted features can be based on one another.

Autoregressive method is Suitable for Signal with sharp spectral features and the analysis method is Frequency domain, and the advantages of this method are:

- AR limits the loss of spectral problems and yields improved frequency resolution
- Gives the good frequency accuracy.
- Spectroscopy based on the AR model is particularly useful when short data segments are analyzed, as the frequency accuracy of the AR spectrum is analytically derived and does not depend on the length of data analyzed.

The disadvantages of this method are:

- It is difficult to select the typical arrangement in the AR spectral estimate of the frequency.
- The AR method will give weak spectral estimates once the estimated model is not appropriate, and the model commands are incorrectly selected.
- They are easily susceptible to heavy biases and even large fluctuations.

5. CONCLUSION

The main aim of this thesis is to investigate feature extraction methods for electroencephalogram EEG signals processing to brain computer interface. There are several ways to make connections between human and some external devices, one of those way is (BCI). In this thesis has five different methods discussed for electroencephalogram (EEG) signal processing, each one different with other, each one has some advantages and disadvantages such as connection speed, loss of important data, there is two type of signal domain like Frequency and time-frequency domain. Each one has a different method of analyzing EEG signals. Frequency domain ways don't offer high-quality performance for a few electroencephalogram signals whereas time-frequency strategies will not offer elaborate info regarding electroencephalogram information the maximum amount as frequency domain strategies. Hence in line with completely different mental task connected applications correct technique ought to be chosen for higher results. And each one of those methods has a different performance like Frequency Resolution and Spectral leakage.

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CURRICULUM VITAE(CV)

Name: **Dindar Issa Saeed**

Address: Zakho, Iraq

Phone number: 0750-401-41-27

E-mail: d.dindarsindi@gmail.com

Date of birth: 07/11/1987

Gender: Male

Marital status: Married

Education and professional training

Newroz University, College of Science

Academic Qualifications:

- B. Sc. (Computer & Information Technology /Computer Science) 2013-2014

- Master Student (Department of Computer Engineering at Firat University) – Turkey

- Lecturer at Duhok Poly Technical (Zakho Technical Institute)

- Employee at the University of Zakho

Skills

Language (Kurdish, Arabic, English, Turkish)

Computer Skills

- Operating systems: **(Windows, Linux, Mac OS X)**
- Computer Programming Language: **(Java, C, C++, C#, SQL, JavaScript)**
- Microsoft Office: **(Word, Excel, Access and PowerPoint)**
- Database: design, analyze, implement and maintain **(Access, Oracle, MS SQL server, etc...)**

-Web Development/Design: **(Drupal, WordPress, PhpMyAdmin, HTML, CSS, JavaScript, PHP, etc...)**

- Networking: Maintenance, troubleshooting problems and working with **(cisco packet tracer)**
- Software Engineering: Design and implement software's
- Solving Computer Problem: **(Hardware and Software)**
- Mobile Application: Working with **(Netbeans, eclipse and android studio)**

-working with software: **(MATLAB, Visual Studio, Adobe Dreamweaver and adobe photoshop, etc...)**