CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

This chapter, discusses the background literature on the biometric, EEG characteristics, EEG, feature extraction and classification algorithms based on neural networks.

2.2 BIOMETRIC

Any biological or physiological signal like a fingerprint, retinal scan or speech matching (Paranjape et al., 2008) that can be used to identify a person (Jain et al. 2004) is called biometric. A biometric system is used for the recognition features, possessed by the person. Human behavior is an area of research in psychological studies (Jain et al., 1999) focused on understanding the conscious or unconscious reaction of the human being in relation to his environment. Behavior happens in time. Behavior is the basis for this research. When a trait is related to a dynamic action of the user, it is called as a behavioral biometric trait. Biometrics is the science of automatically identifying individuals based on their unique physiological or behavioral characteristics. These characteristics are also called biometric identifiers and they must be distinctive and measurable in order to identify individuals. Biometrics systems which are based on fingerprints, iris, palm print, retina, and face are widely used in diversity of area for user authentication; these approaches are gaining much popularity in the technology world. Unfortunately, they have caught with some abatement which degrades its performance (Woodward et al., 2003). One of the main differences between physical and behavioral biometric is the exploitation of the information, content across time in behavioral biometrics, as opposed to the commonly used instant acquisition in physical traits. There are two types of biometric systems that enable the link between a person and his / her identity includes verification and identification (Jain et al., 2004).
Discrete Wavelet Transform (DWT) with logarithmic Power Spectral Density (PSD) is combined for speaker formants extraction, to be used as evident classification features by (Daqrouq et al. 2009). For classification, Feed Forward Back Propagation Neural Network (FFBNN) method is proposed. The Discrete Wavelet Formants Neural Network (DWFNNT) system works with excellent capability of features tracking even with 0dB Signal-to-Noise Ratio (SNR). The results show excellent performance with 93.21% Recognition Rate (RR).

2.3 BIOLOGICAL MEASUREMENTS

Any biological measurement, analysis and many other factors contribute to the success or failure of the process. All of these factors fall into two general categories: properties of the characteristics measured and properties of the measurement process. So, any human physiological or behavioral characteristic can be used as a biometric characteristic as long as it satisfies the following requirements:

i. **Uniqueness**: No two persons should have the same characteristic, and each relevant person should only have one original characteristic.

ii. **Universality**: This characteristic must exist in all individuals in the population being measured.

iii. **Permanence**: This characteristic should be time-invariant and must be a permanent part of the individual.

iv. **Authentication**: The characteristic must be able to match against similar characteristics and a positive or negative match must be able to be made based on the measurement.

v. **Collectability**: The characteristic can be measured. However, in a practical biometric system, i.e., a system that employs biometrics for personal recognition, there are a number of other issues to be considered, including:

   - **Performance**: Refers to the achievable recognition accuracy and speed, the resources required to achieve them, as well as the operational and environmental factors that affect the accuracy and speed.
Acceptability: Indicates the extent to which people are willing to accept the use of a particular biometric characteristic in their daily lives.

Circumvention: Reflects how easily the system can be fooled using fraudulent methods. The practical biometric system should meet the specified recognition accuracy, speed, and resource requirements, be harmless to the users, be accepted by the intended population, and be sufficiently robust to various fraudulent methods and attacks to the system (Jain et al., 2004).

2.4 BIOMETRIC MODALITIES

Biometric systems are divided on the basis of the authentication medium used. They are broadly divided as identifications technology as given:

- Fingerprints,
- Face Recognition,
- Palm Print
- Iris
- Voice Recognition.

2.4.1 Finger Print

Finger prints are the tiny ridges, whorls and valley patterns on the tip of each finger. Finger print recognition is one of the most adopted techniques for user identification. This is considered as a most reliable, feature and the cost of implementing finger print recognition method is very less than other biometric features. It is used in many forensic and commercial applications such as criminal investigation, electronic personal ID cards, etc. (Sravya et al., 2012). The finger print is the pattern of ridges and valleys on the tip of a finger and is used for personal verification of people. Fingerprint based recognition method is used because of its relatively outstanding features of universality, permanence, uniqueness, accuracy and low cost has made it most popular and a reliable technique and is currently the leading biometric technology (Jain et al., 2004).
Robust alignment algorithm is addressed to align fingerprints and measures similarity between fingerprints by considering both minutiae and orientation field information. Alignment between a latent and a rolled print is a difficult problem because latent often contain a small number of minutiae and undergo large skin distortion. Using these two problems, they proposed the Descriptor-Based Hough transform (DBHT), which is a combination of the generalized Hough transforming and a local minutiae descriptor, called Minutia Cylinder Code (MCC) (Alessandra et al., 2013). Automated Fingerprint Identification Systems (AFIS) which had played an important role in many forensics and civilian applications. The baseline matching algorithm took only minutiae as input and consists of the following steps: 1) Local minutiae matching 2) Global minutiae matching 3) Matching score computation. The minutiae-based baseline improved to extended features was used. A pair of fingerprints is classified by Support Vector Machine (SVM). Limitation of the proposed method is the poor quality of ridge impressions (Jain et al., 2014). The Gradient based approach was proposed by (Aggarwal et al., 2008) that capture textural information by dividing each minutiae neighborhood locations into several local regions of which histograms of oriented gradients are then computed to characterize textural information around each minutiae location. A texture feature of energy of a fingerprint can be used for effecting fingerprint verification (Jhat et al., 2011).

### 2.4.2 Face Recognition

Face recognition technique records face images through a digital video camera and analyses facial characteristics like the distance between eyes, nose, mouth, and jaw edges. These measurements are broken into facial planes and retained in a database, further used for comparison. Face recognition can be done in two ways such as face appearance and face geometry (Chellappa et al., 1995). Principal Component Analysis (PCA) is used, a feature extractor for face recognition by (Kirby et al., 1990). The main objective of the neural network in the face recognition is the feasibility of training a system to capture the complex class of face patterns. The neural networks are nonlinear in the network and so it is the widely used technique for face recognition. The authors achieved 96.2% accuracy in the face recognition process when using 400 images of 40 individuals.
The drawback of the neural network approach arises when the number of classes increases. (Karungraru et al., 2004) proposed template matching in which other face templates can be exploited from different prospects to characterize single face. The 188 images are extracted from 47 subjects. The pattern matching algorithm is a very practical approach, very simple to use and approximately achieves 100% recognition rate. The PCA using Eigen face provides the linear arrangement of templates. The complexity arises only during the extraction of the template.

2.4.3 Palm Print

A palm print refers to an image acquired from the palm region of the hand. The palm itself consists of principal lines, wrinkles and epidermal ridges and can be used for personal verification (Zhang et al., 2004). There are two types of palm print verification system namely high resolution and low resolution. Palm prints can be used for criminal, forensic, or commercial applications (Shu, 1998). The competitive coding scheme is used for palm print. This scheme extracts the orientation information from the palm lines and stores it in the competitive code. The proposed coding scheme has been evaluated using a database with 7,752 palm print images from 386 different palms. For verification, the proposed method can operate at a high genuine acceptance rate of 98.4% and a low false acceptance rate of 3*10^-6 (Kong et al., 2011).

A novel algorithm for the automatic classification of low-resolution palm prints is experimented by (Huang et al., 2008). The local information about the extracted part of the principal line is used to decide a Region of Interest and then a suitable line detector is chosen to extract the next part of the principal line in this Region of Interest (ROI). The palm prints are classified into six categories considering the number of the principal lines and their intersections. From the statistical results in the database containing 13,800 palm prints, the proposed algorithm classified these palm print with 96.03% accuracy. This palm print authentication methods require that the input palm print should be matched against a large number of imprints in a database, which is very time consuming. A high resolution approach
for palm print recognition with multiple feature extraction is done by (Dai et al., 2012). For orientation estimation the Discrete Fourier Transform (DFT) and radon-transform-based orientation estimation is used. For minutiae extraction, Gabor filter is used for ridges enhancement according to the local ridge direction and density. To extract the principal line features, Hough transform is applied. SVM is used as the fusion method for the verification system and the proposed heuristic rule for the identification system. However the proposed systems are based on encoding and matching creases, which are not as reliable as ridges.

2.4.4 Iris

The iris is a thin circular diaphragm, which lies between the cornea and the lens of the human eye, responsible for controlling the diameter and size of the pupil and thus the amount of light reaching the retina. The eye color is defined by the color of the iris. In optical terms, the pupil is the eye's aperture and the iris is the diaphragm that serves as the aperture stop (Flom et al., 1987). Iris biometrics system performance on a larger dataset based on the Gaussian Model constructed from a smaller data set. The database contains “non-ideal” iris images of 108 irises with 6 images per iris. They formed 54 vectors, each of size 6 and 108 vectors, each of size 3 samples of genuine. The distance between a pair of Iris subjects is defined as a K-dimensional Hamming Distance, modeled as Gaussian distribution. Database resulted in a reduction of the search space by an average of 84% at a 100% hit rate. The main factor for the amount of speedup during verification was the penetration rate of the indexing (Schmid et al., 2006).

Automated biometric iris recognition is where segmentation and matching process are implemented using Histogram Equalization and Gaussian smoothing filter. The experiment was performed with a sample of 67 grayscale images which were selected from the Chinese Academy of Sciences Institute of Automation (CASIA) database. Because of this, few pixel spaces between iris and pupil center, contour is wrongly segmented by the Hough transform. Subsequently, with adjusted parameters and Hough transform with SURF technique, satisfactory result was obtained. This system handles users falling into the Fail to Enroll (FTE) category (Sonia Sangwan et al., 2015). A biometric security technique for Integer
Wavelet Transform based Human Recognition System (IWTHRS) using iris images verification. Data set contains 756 gray scale eye images with 108 unique eyes or classes and 7 different images of each unique eye. The features of the normalized Iris are extracted using Integer Wavelet Transform and Discrete Wavelet Transform. The Hamming Distance is used for matching of two iris feature vectors. It is observed that the time required for feature extraction in case of IWTHRS is more when compared DWT based Human Recognition System (DWTHRS) (Prashanth et al., 2009). Iris encoding is generated from the inner product of the output from a 1D Log Gabor filter and secret pseudorandom numbers. In the segmentation stage, first an edge map is generated using a Canny edge detector. A Circular Hough Transform is used to obtain the iris boundaries. The isolated iris part is unwrapped into a rectangle with a resolution of 20 * 240 using Daugman’s rubber sheet model. In matching, Hamming Distance is used to indicate the dissimilarity between a pair of iris codes. The sampling the iris patterns requires much users cooperation (Chin et al., 2006).

2.4.5 Voice Recognition

Our voice is influenced by the characteristics of the format of our body, by the physical constrains the body produces in the sound wave, and by the temporal characteristics derived from our cognitive processing and timing of sound producing. Inherent properties of the speaker like fundamental frequency, nasal tone, cadence, inflection, etc. are used for speech authentication (Hebert, 2008). GMM are used for authentication of speaker verification system. For each frame, a dimensional feature vector is extracted, the Discrete Fourier spectrum is obtained via a Fast Fourier transform from which magnitude squared spectrum is computed and put it through a bank of filters. The Mel-scale Cepstral Coefficients are computed from the outputs of the filter bank. GMM classifier is used. GMM-based density estimation achieves a significant recognition rates due to low FAR (False Acceptance rate) and FRR (False Rejection Rate). Possibility in rare case voice is lost (Mohamed Soltane et al., 2010). A hybrid scheme which appropriately incorporates the advantages of both the generative and discriminant model paradigms is described and evaluated by (Rafik Djemili et al., 2007). Support Vector Machines (SVMs) are trained to divide the whole speakers’ space into small subsets of speakers within a hierarchical tree structure. During testing a speech
token is assigned to its corresponding group and evaluation using Gaussian Mixture Models (GMMs) is then processed. A significant improvement compared to the baseline system is reported, a relative reduction in identification error rate up to 50% is reached, independently, neither on the training data size nor on the testing utterances lengths

2.5 BACKGROUND KNOWLEDGE RELATED TO ELECTROENCEPHALOGRAM

Electroencephalogram (EEG) is a record of the electrical activity of the brain and is a tool which gives an insight into the brain functions thereby helping the physicians to diagnose various abnormalities. Recording electrical oscillations of the brain began in 1875, when the British neuropathologist Richard Caton first recorded the electrical activity of the brains of rabbits and monkeys directly from the brain tissue Caton 1875. The first human EEG was recorded in 1924 by Hans Berger, a German psychiatrist Berger 1929 (Collura, 1993). Since the days of Berger and the verification of his recordings by Jasper and Carmichael 1935, EEG has taken its place as a standard laboratory investigation in clinical neurophysiology and neurology. It is used in the diagnosis of brain pathology, e.g., epilepsy, sleep disorders and disorders of the nervous system. EEG recording is also used extensively in psychophysiological research and in the testing of drugs pharmacology Pryse-Phillips 1997. Already at that time, Berger noticed that brain waves varied with the individual’s state of consciousness (Tyner, 1989).

During the EEG test by (Niedermeyer et al., 1993) a number of small discs called electrodes are placed to different locations on the surface of the scalp with temporary glues. Then each electrode is connected to an amplifier (one amplifier per pair of electrodes) and an EEG recording machine. The electrical signals from the brain are converted into wavy lines on a computer screen to record the results. EEG recordings, depending on their use, can have from 1 to 256 electrodes recorded in parallel, which is called multichannel EEG recordings. One pair of electrodes usually makes up a channel. Each channel produces a signal during an EEG recording.
There are two types of EEG depending on where the signal is taken in the head: scalp or intracranial. For the scalp EEG, small electrodes are placed on the scalp with good mechanical and electrical contact. Special electrodes implanted in the brain during the surgery result in intracranial EEG. On the other (Bronzino, 1995) the EEG measured directly from the cortical surface using subdural electrodes is called the Electrocardiogram (ECG). The amplitude of an EEG signal typically ranges from about 1 to 100 µV in a normal adult, and it is approximately 10 to 20 mV when measured with subdural electrodes such as needle electrodes. Since the architecture of the brain is non-uniform and the cortex is functionally organized, the EEG can vary depending on the location of the recording electrodes (David Millet et al., 2001).

2.6 EEG CHARACTERISTICS

EEG measures brain waves of different frequencies within the brain. EEG signals are sinusoidal waves, their amplitude is normally between 0.5 and 100 µV. After applying a Fourier Transform to the raw signals, the power spectrum is generated for four groups of waves. In general, EEG signals represent the combination of waveforms, and are generally classified according to their: Frequency, Amplitude (power), wave morphology (shape), spatial distribution topography and reactivity (behavioral state) (Bronzino et al., 1995).

2.7 FREQUENCY BANDS

The most familiar classification uses EEG waveform. These waveforms are essential tools for analyzing human brain activity. The raw EEG is usually described in terms of frequency bands are shown in Figure 2.1.

2.7.1 Delta Waves (Less than 4 Hz)

These are large amplitude waves, which occur in deep sleep and are associated with some abnormal processes and are said to reflect the unconscious mind. Delta waves are found in infants up to about one year of age and are present in stages 3 and 4 of sleep. These waves
produce immobile, lethargic and less attentive states. Delta activity is usually most prominent frontally in adults and posteriorly in children (Nunez, 1995).

2.7.2 Theta Waves (4 Hz to 8 Hz)

Theta is also classed in the 'slow' category and occurs in connection with creativity, emotions, intuition and is associated with the subconscious mind. While theta waves are abnormal in awake adults, they are perfectly normal in children up to 13 years of age and in sleep. It is usually regional in spread, may involve many lobes, and can be lateralized or diffuse.

2.7.3 Alpha Waves (8 Hz to 13 Hz)

Alpha is a common state of the brain and occurs whenever a person is alert. It is a marker for alertness and sleep, but not actively processing information. Alpha has been linked to extroversion introverts show less, creativity subjects show alpha when listening and coming to a solution for creative problems and mental work. They are strongest over the occipital back of the head cortex and also over frontal cortex.

2.7.4 Beta Waves (13 Hz to 30 Hz)

These are low amplitude or 'fast' waves and are found during the waking state as well as when the brain is working as in some calculation or thinking process. It reflects desynchronized active brain tissue. It is usually seen on both sides of the cortex in symmetrical distribution and is most evident frontally. It may be absent or reduced in areas of cortical damage. Low beta activity 12-15 Hz is localized by side and by lobe and represents a relaxed yet alert state; Range beta 15-18 Hz is localized over several areas often associated with thinking and finally, High beta above 18 Hz corresponds to a strongly localized activity leading to agitated mental activity such as planning, math calculation etc. (Ridderinkhof et al., 2003).
2.7.5 Gamma Waves (36 Hz to 44 Hz)

This is the only frequency group distributed over every part of the brain. It is hypothesized and in some cases validated that the 40 Hz activity in the brain consolidates the required areas for simultaneous processing whenever the brain needs to access information from multiple regions. A good memory is associated with well-regulated and efficient 40 Hz activity, whereas a 40 Hz deficiency creates learning disabilities (Miltner et al., 1999).

![Figure 2.1 Different types of normal EEG rhythms (Lotte, 2009).](image)

2.8 ELECTRODE PLACEMENT CONFIGURATIONS

Standardized electrode placement scheme known as the International 10-20 system (Jasper et al., 1958) was established, allowing the comparison of different EEG data derived from different subjects. This universal arrangement of electrodes known as the international ten twenty system, assures reproducible electrode sites with sufficient coverage of all parts of the head as depicted (Manzoor Khazi et al., 2012). The different electrode positions are
derived from measurements taken between standard landmarks on the skull (Sabarigiri, 2014). These measurements allow the calculation of a network of lines, which are superimposed across the head. Electrodes are placed where the lines of this mesh intersect. This results in inter-electrode distances of ten and twenty percent of a line's total length. In this convention, each electrode site has a letter identifying its sub-cranial lobe i.e. Fp - Front polar or prefrontal lobe, 'F' - Frontal lobe, 'T' - Temporal lobe, 'C' - Central lobe, 'P' - Parietal lobe, 'O' - Occipital lobe. In addition, there is a number or another letter identifying its hemispherical location. The subscript 'Z' denoting line zero ensuing any lobe abbreviation refers to an electrode placed along the cerebrum's midline. The use of an even number 2, 4, 6 or 8 represents the right hemisphere and odd numbers 1, 3, 5 or 7 referring to the left hemisphere (Teplan, 2002).

The numbers rise with increasing distance from the midline of the head. The distances are calculated as percentages of typical lengths such as the head circumference etc. Percentages are made use of because the skull varies from subject to subject. An adolescent may be smaller than an adult and also traumatic accidents to the skull may have occurred in the subject's history creating an out of proportion condition (Schalk et al., 2004). The percentage relationship remains the same for the location of the internal brain lobes. Skull dimensions are measured accordingly in centimeters and then site distances or spacing are converted with the 10% and 20% factors. Fifty percent is used frequently, but is a composite of 10, 20 and 20%. Supplementary electrodes to those typically employed in the 10-20 system have been devised to improve electroencephalographic spatial resolution. This more extensive placement scheme using Modified Combinatorial Nomenclature (MCN) was developed by the American Clinical Neurophysiology Society and it broadens the 10-20 system by subdividing the existing inter-electrode distances as in the Figure 2.2 (Srinivasan et al., 1998).
In recent times, the limited spatial resolution of the conventional EEG technology has been tackled by introducing High Resolution EEG HR-EEG (Babiloni et al., 1997; Edlinger et al., 1998). A pre-requisite for such methods is adequate sampling of the potential distribution on the scalp surface. The point-spread function of conduction of potential from the brain surface to the scalp averages about 2.5 cm (Gevins, 1990). Thus to adequately cover the surface of the scalp with electrodes having inter-electrode distance in this range, EEG equipment supporting at least 128 channels is required (Srinivasan et al., 1998). In accordance with this need, the state-of-the-art technology in EEG recording uses machines with up to 256 electrode positions.

2.9 SIGNAL ANALYSIS

Anything which carries some information is called a signal. However to derive useful information from the raw signal it demands a kind of standard way of representation. In order to represent a raw signal in a standard notation, the signal has to undergo a series of operation. The serious operation together is called as “signal processing”. There are three basic ways in which the signals are analyzed by (Blanco et al., 1995). There are Time Domain analysis, Frequency Domain analysis and Time and Frequency Domain analysis.
Person identification and person authentication are two different types of applications and thus pose different challenges on decision making of biometric systems. The goal of person identification is to identify an individual from a group of persons, i.e. matching the biometric features of one person against all the records in a database, while the goal of person authentication is to confirm or deny an identity claim by a particular individual. We are particularly interested in person authentication in this thesis. An authentication and identification system often consists of two main components, they are EEG feature extraction and pattern identification.

A two-stage threshold method to verify 5 subjects was proposed by (Palaniappan et al., 2008) based on the features of Autoregressive Coefficients (AR), channel spectral powers and Inter-Hemispheric Channel Spectral Power Differences (IHPD), Inter-Hemispheric Channel Linear Complexity (IHLC), and non-linear complexity on 6 channels. This method reached a False Reject error (FRE) ranging from 0 to 1.5%. The EEG signal recorded during the performance of three mental tasks to identify six subjects. Power spectral density feature using Welch algorithm is extracted from the EEG beta waves this was proposed by (Hema el al., 2008). Feed Forward Neural Classifier is used to achieve an average authentication rate of 97%.

The use of PSD as the feature, the statistical framework is done based on Gaussian Mixture Models (GMM) and Maximum a Posteriori Model (MAPM) Adaptation on speaker and face authentication. The potential of their method is shown by simulations using strict train and test protocols and results. Person identification based on spectral information is extracted from the EEG is addressed by (Poulos et al., 2001). The proposed method has yielded correct classification scores in the range of 80% to 97% showing evidence that the EEG carries genetic information for person identification. Research proposed (Ravi et al., 2005) utilized the 40 Hz EEG oscillations related to the visual processing for subject identification. Visual Evoked Potential (VEP) was recorded from 20 subjects while they were looking at a picture. PCA was applied; fuzzy ARTMAP, k-nearest neighbor, and back
propagation network classifiers were used attaining performance of up to 95% with 61 electrodes were used to record the EEG signals.

The 40 Hz EEG oscillations related to the visual processing for subject identification. VEP was recorded from 20 subjects while they were looking at a picture. PCA was applied; Fuzzy Adaptive Resonance Theory (F-ARTMAP), k-nearest neighbor, and back propagation network classifiers were used for identification and attaining performance of 95% with 61 electrodes EEG recordings (Ravi et al., 2005). Biometric identification systems are summarized by (Poulus et al., 1999a; Poulus et al., 1999b). Recorded EEG signals from 1 channel of 4 subjects resting with eyes closed. They applied parametric processing and computational Geometry and achieved 84% and 91% respectively. EEG as an authentication tool which is used by (Riera et al., 2008). Data collected from 51 subjects and 36 intruders. Equal error rate (EER) of 3.4% is obtained, True Acceptance Rate (TAR) of 96.6% and a False Acceptance Rate (FAR) of 3.4%. (Poulos et al., 1998; Poulos et al., 1999) proposed a method to distinguish an individual from the rest using EEG signals. They performed a parametric spectral analysis of α band EEG signals by fitting to them a linear all-pole autoregressive model. The coefficients of the fitted model were then used as features for the identification component. In (Poulos et al., 1998) the identification component was built with computational geometric algorithms and (Poulos et al., 1999) they changed it to a neural network, namely for a Kohonen’s Linear Vector Quantizer (Kohonen et al., 1989). The cerebral activity was recorded from subjects at rest, with closed eyes using single channel EEG for three minutes.

Maximum a Posterior (MAP) trained Gaussian models on the EEG classification. Band data were preprocessed by a spline Laplacian filter prior to the PSD computation. Authentication possibilities were tested; identification scores in the ranges of 60% to 100% were achieved. Interestingly, the authors observed a degradation of the identification performance over days (Marcel et al., 2007). Biometric identification with EEG were recorded over 14 electrodes placed over the whole scalp; EEG is parameterized using a 1358 dimensional feature vector composed of autoregressive coefficients, Power Spectral Density, integrated spectral power, inter hemispheric power differences, and inter hemispheric linear
complexity. SVM is used for EEG data classification. Classification scores in the range of 97% is achieved (Ashby et al., 2011). A multimodal authentication algorithm based on EEG and Electrocardiogram (ECG) signal is done by (Riera et al., 2010). They conducted tests on 40 healthy subjects. Each subject was required to sit in a comfortable armchair, to relax, be quiet and open their eyes. Features were extracted using auto regression and Fourier Transform. The classifier used in the authentication process is the classical fisher’s discriminate analysis. True Acceptance Rate (TAR) of 71.9% and a False Acceptance Rate (FAR) of 21.8%.

EEG as a potential biometric for personal Identification has been studied by Marios S.Poulos since 1998, and colleagues were EEG biometrics when in 1999. They presented an automatic person identification system that was based on EEG signals acquired from four subjects in a resting state with closed eyes, closed eye position and the resting state of the brain wave acquisition protocol has used for biometric authentication. Autoregressive (AR) stochastic modeling and polynomial regression based classification with an accuracy of 97% (Daria La Rocca et al., 2012). A short time Principal Component Analysis on overlapping window segments and non overlapping window segment is performed to extract the feature. A Recurrent Neural Network (RNN) based classification of EEG features is proposed by (Hema et al., 2007). The results validate the feasibility of classifying EEG patterns related to mental task. Average classification accuracy of 97.5% was obtainable.

A multiple mental thought authentication model. The experiment was conducted on four subjects. An Electro-Cap elastic electrode cap was used to record EEG signals from positions C3, C4, P3, P4, O1 and O2 defined by the 10-20 system of electrode placement. Six, AR coefficients were obtained for each channel, giving a total of 36 feature vector for each EEG segment for a mental thought. Linear Discriminate Classifier was used to classify the EEG feature vectors; LDC is a linear classification method that is computationally attractive as compared to other classifiers like artificial neural network (Palaniappan et al., 2006). LVQ for user identification. The algorithm was conducted on a dataset of 8 subjects. Linear magnitude spectra of the single segments were computed by Fast Fourier Transform Hamming window was used. The LVQ neural network is a self–organizing neural network,
with an added second layer for vector classification intended to be used by unlabeled training
data. Hence LVQ network is a kind of nearest-neighbor classifier; it does not make clusters,
but the algorithm search through the weights of connections between input layer neurons and
output map neurons. The best classification rate was around 80% (Cempirek et al., 2007).

The Common Spatial Patterns (CSP) are employed to carry out energy feature
extraction by (Sun et al., 2008). The system was tested on 9 subjects. The task was to imagine
moving his or her left or right index finger in response to a highly predictable visual cue.
Based on these features, neural network classifiers can be learned. Neural networks of one
hidden layer and one output layer for experiments. The results showed that imagining left
index finger movements is more appropriate for personal identification. The left index
movement gave a classification accuracy of 95.6%. A Multimodal authentication algorithm
based on EEG and Electrocardiogram (ECG) signals proposed by (Riera et al., 2008). They
conducted the test on 40 healthy subjects. Three features were selected from the synchronicity
features, namely; Mutual information, Coherence and Correlation measures. The classifier
used in the authentication process is the classical Fisher’s Discriminant Analysis, Four
different discriminant functions were used (Linear, Diagonal Linear, quadratic, diagonal
quadratic). After combining the 2 signals (EEG and ECG) the TAR is 97.9% and the FAR is
0.82%.

Wavelet Packet Transform (WPT) was used for feature extraction of the relevant
frequency bands from the raw EEG signals. The two classifiers used were Radial Basis
Function Neural Network (RBFNN) and Multilayer Perceptron Back propagation Neural
Network. RBF Neural Network has better performance as compared to MLP-BP NN with
Resilient back propagation method for classification. Average accuracy was obtained 100%
by using RBFNN classifier (Vijay Khare et al., 2010). EEG signals were measured using 64
electrodes and sampled at 256 Hz for 1 second. Univariate autoregressive model is used as
feature extractor and model order of 4 appeared to be optimal. Subject verification is done
using a linear SVM classifier. The subjects were identifiable to 99.76% accuracy (Katharine
Brigham et al., 2010).
The data collected from two subjects were used in this study. Subjects were aged between 21 and 48 years. EEG signals are obtained from two subjects. On performing the PCA transform 6 features per window matrix per task. The RNN is trained using the Practical Swarm Optimization (PSO) algorithm to classify the EEG signals into two mental tasks. Average classification accuracies obtained with the PSO RNN vary from 82.5% to 93% (Hema et al., 2008). The eye blinking signal is extracted and applied for identification and verification tasks. The raw signal was collected from 25 healthy, non-alcoholics, subjects. Four groups of features (G1, G2, G3, and G4) were extracted based on time delineation of the eye blinking waveform. Different classifiers like Vector Quantization (VQ), Gaussian Mixture Modeling (GMM), and Discriminant Analysis (DA) based on linear or quadratic boundaries, and SVM were tested for the proposed system by (Chen et al., 2006). Identified subjects with best accuracy of 95.3%.

Data were collected from 10 male subjects while resting with eyes open and eyes closed in 5 separate sessions conducted over a course of two weeks. Features were extracted using the wavelet packet decomposition subsequently; the neural network algorithm is used to classify the feature vectors. Results show that 2– channel system using only the C3 and C4 channels outperformed then 4– channel biometrics system with a classification accuracy of 81% (Muhammad Kamil Abdullah et al., 2010).

Gamma Band Spectral Power (GBSP) features extracted from VEP signals recorded from 61 channels while subjects perceived a picture. Researchers applied PCA to reduce noise and background EEG effects as the first step. During the second step, the GBSP of each channel was normalized by the total GBSP. For the classification, namely Simplified Fuzzy ARTMAP (SFA), Linear Discriminant (LD) and k-Nearest Neighbor (KNN). KNN gave improved results through the use of PCA with classification performance of 96.5% (Palaniappan et al., 2005). The effectiveness of the EEG as a biometric for the person identification of individual subject in a pool of 40 normal subject mention by (Paranjape et at. 2001). The AR coefficients in these models are then evaluated of their biometric potential. Discriminant function applied to the model coefficients are used to examine to which the subjects in the data pool can be identified. In this data pool 90% correctly identified. Brain
Computer Interface (BCI) research from laboratory to real world application study conducted by (Wenjie XU et al., 2004) presents a high accuracy of the EEG signal classification method. EEG signal into a spatial pattern applies the Radial Basis Function (RBF) feature selection method to generate robust feature. Classification is performed by the SVM which obtained a classification rate of 90%.

Researches (Poulos et al., 1999) experimented classification of a person as one of a finite set of known persons. In the tests they recorded 45 EEG features from each of 4 individuals (the X set) and one EEG feature from each of 75 individuals (the non-X set). The neural network was trained using 20 features from each X member and 30 features from non-X members. Then the system was used to classify the remaining 25 features of each X member and the 45 features from the remaining non-X members. This process was repeated for all the 4 X members, attaining a correct persons verification score between 72% and 84%. EEG-base person authentication is first proposed by (Marcel et al., 2007). They proposed the use of PSD as the feature, and a statistical framework based on GMM and MAP Model Adaptation.

2.11 MULTIMODAL BIOMETRICS BASED ON IDENTIFICATION AND VERIFICATION SYSTEM

The framework for multimodal biometric person authentication developed by (Jain et. al., 2004). Even though some of the traits offering good performance in terms of reliability and accuracy, none of the biometrics is 100% accurate. With the increasing global need for security, the demand for robust automatic person recognition systems is evident. For applications involving the flow of confidential information, the authentication accuracy of the system is always the priority concern. From this basic reason the use of multimodal biometrics is encouraged. Multi biometrics are an integrated prototype system embedding different types of biometrics. Multimodal biometric fusion and identity authentication technique help to achieve an increase in performance of identity authentication system. A Bimodal biometric systems using speech and face features and tested its performance under degraded condition. Speaker Verification (SV) system is built using Mel-Frequency Cepstral Coefficients (MFCC)
followed by delta and delta-delta for feature extraction and Gaussian Mixture Model (GMM) for modeling. A Face Verification (FV) system is built using the combination of Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA). Sum rule is used for the fusion of the biometric scores. The performance of the SV system under the degraded condition is also checked. All the experimental results are shown upon a subset of IITG-DIT M4 multi-biometric database. The complementary information derived from the speech biometric at training stage is used to further decrease the FV error rate, which is termed as Cohort fed FV system. Finally, we propose an improved bimodal person authentication system using SV and Cohort fed FV biometric systems (Soyuj Kumar Sahoo et al., 2005).

Electrocardiogram (ECG) and Phonocardiogram (PCG) signals are not only useful for medical purposes, but can also be applied for biometric identification and verification. A group of 20 subjects are modeled by the system, and for heart sound. The database is divided into groups of training and test data. Speech: The same set of clients and impostors are used in speaker recognition. Mel Frequency Cestrum Coefficients (MFCC) were used as the feature representation of the heart and speech signals. 12 MFCCs per frame are used for the classification step. Speaker Identification (SI) model is 99.3% and Electrocardiogram Identification (ECGI) 98.5%. From the result speaker Identification out performed ECGI (Osamah Al-Hamdani et al., 2013).

From the survey, it is observed that the limitations using the conventional biometrics include that they are unique identifiers, but they are not confidential and neither secret to an individual. For example, people leave their physical prints of finger on everything they touch, iris patterns can be observed anywhere they look, faces are visible, and voices are being recorded. The presence of biometric prints publicly, offering intruders to lift these prints and copy them as real, thus spoofs the system. One of the main advantages of using EEG signals as biometric is that the reproduction of the EEG signals is very difficult until the same individual is not called for the re-enrollment. Therefore, the proposed methods using the EEG as biometric are sufficiently non vulnerable to spoof attacks.
2.12 SUMMARY

This chapter provides an overview of EEG signal classification and also provides necessary background knowledge related to the EEG. Then this chapter discusses about the classification of EEG signals and also reviews which methods were used for the EEG signal classification in the previous study. From the literature review of the EEG signal classification, it can be concluded that there are still some limitations associated with the existing methods. Hence developing feature extraction and classification algorithms are needed for person authentication. The experimental setup and data acquisition for single channel and two channel system procedure are discussed in the following chapter.