Development of Biometric Verification Algorithm using Electroencephalogram (EEG)

A thesis submitted
in fulfillment of the requirement for the award of degree
of
Doctor of Philosophy

Submitted by

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DECLARATION

I hereby declare that the thesis entitled **"Development of Biometric Verification Algorithm using Electroencephalogram (EEG)"** which is being submitted to Department of Electrical and Instrumentation Engineering, Thapar University, Patiala in the partial fulfillment of the requirement for the degree of **Doctor of Philosophy,** has previously not formed the basis for the award of degree, diploma, fellowship or any other similar title. It is certified that the thesis is entirely my own and that the idea and references cited herein have been duly acknowledged.

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CERTIFICATE

Certified that the thesis entitled "**Development of Biometric Verification Algorithm using Electroencephalogram (EEG)**" being submitted by **Mr. Puneet Mishra** to the **Department of Electrical & Instrumentation Engineering, Thapar University, Patiala** in fulfillment of the requirements for the award of degree of "**Doctor of Philosophy**" is a record of bonafide research work carried out by him. He has worked under my guidance and supervision and fulfilled the requirements for the submission of this thesis, which has reached the requisite standard. The matter presented in this thesis has not been submitted in part or full for the award of any degree in any other University or Institute to the best of my knowledge.

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(Puneet Mishra)

ABSTRACT

The biometrics is one of the most innovative areas of Science dealing with the automatic identification/verification of the person in the modern world. It involves the measurement of physiological and behavioral characteristics of a person for authentication. The conventional biometrics (e.g. fingerprint, voice, hand geometry etc.) are prone to forgery and can be spoofed by imprinting artificial finger, voice imitation, and fake signature etc. Moreover, the presence of an object is not guaranteed in conventional biometric systems. Such problems lead to uncover alternative and effective biometric traits which are more accurate, reliable and secure for authentication of an individual. The bio-signals are unique, confidential, secure, almost impossible to mimic, hard to be copied and guarantees the individuals presence during acquisition of signals. In this thesis, EEG signals were used for biometric verification because, apart from basic characteristics of a biometric system (i.e. universality, uniqueness etc.), it possess attributes of liveliness detection due to presence of a legitimate individual for signals acquisition. Moreover, the EEG records brain waves which are unique and cannot be read by others. In this way, EEG is non-vulnerable to spoof attacks and thus, highly reliable for person identification/verification. Keeping in mind the specific traits of EEG signals, this thesis was focused on the development of a system for person verification using EEG signals. The entire study is briefly explained below.

The database consists of 1960 samples (acquired/standard) from 67 subjects in three categories: (i) *Relaxed State with Eyes Open*: 32 human volunteers with 30 trials per person; (ii) *Alcoholic/Controlled Disposition*: 30 subjects with 30 trials (Standard: Ingber); (iii) *Mental Ability Tasks*: 05 subjects performing 05 different cognitive tasks (Standard: Keirn and Aunon).

After the acquisition, the EEG signals were pre-processed for artefacts elimination (caused by eye blinks) using Fast Independent Component Analysis (FastICA), a multivariate signal statistical technique. It (FastICA) finds the underlying components from the mixture of signals (which are statistically independent and non-gaussian) and decomposes the signals into several components. The application of FastICA resulted in refined EEG signals with an improved *Signal to Noise Ratio* (SNR).

After pre-processing, 20 features were extracted using Linear (Time and Frequency domain) and Non-Linear (Fractal Dimension) techniques. Five features (e.g. RMS, Approximate Entropy, LZ Complexity, Median Power Frequency and Spectral Edge

Frequency) were selected amongst 18 features under linear techniques based upon minimum intra-individual and maximum inter-individual differences using one-way Analysis of Variance (ANOVA). Non-linear techniques (Higuchi Fractal Dimension and Correlation Dimension) were applied on third type of dataset (i.e. mental ability tasks).

For verification, the individual's query samples were compared to previously enrolled data of that person. The verification was carried out on individual's extracted features of time and frequency domain at three levels of security threshold i.e. 5%, 10% and 15% (Higher to Lower security). The maximum Genuine Acceptance Rate (GAR) of 86.12% (LZ Complexity) was achieved in the case of relaxed subjects, whereas, GAR of 87% (SEF) in Alcoholic/controlled disposition. After normalization of features using Minimum Maximum and Euclidean Norm techniques, a further improvement was observed. The normalized datasets were assigned with weights (estimated from Rank Order Centroid method) to find the cumulative score, resulting in maximum GAR of 91.04% (with Euclidean Norm) in relaxed subjects whereas, 91.40% (with Min-Max scaling) in Alcoholic/controlled disposition. Also, an advance machine learning technique (Support Vector Machine-SVM) resulted in Correct Classification Rate (CCR) of 97.51% (FRR-2.49%) and 96.82% (FRR-3.17%) in relaxed and alcoholic/controlled subjects respectively.

Under non linear technique using SVM, the CCR of 97% was observed with HFD features; whereas, 95% with Correlation Dimension in the case of mental ability tasks.

To overcome the limitations of single EEG biometric such as universality (EEG not recorded for epileptic or Alzheimer's patient), uniqueness etc., the EEG data were combined with the Fingerprint at score level using the Fuzzy logic technique. The fusion of the two biometric makes the system more robust, flexible, secure and accurate. The overall Genuine Acceptance Rate (GAR) of 93.2% and FAR of 7% was achieved with the fusion of EEG and Fingerprint.

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LIST OF SYMBOLS

1: M	One to Many
1: 1	One to One
2D	Two Dimensional
3D	Three Dimensional
μV	Microvolt
Hz	Hertz
δ	Delta
θ	Theta
α	Alpha
β	Beta
γ	Gamma
h^2	Heritability Factor
Ψ	Autoregressive Parameters
ε_t	Noise
c	Constant
P300	Oddball Exogenous Stimuli
Th_1	Threshold 1
Th_2	Threshold 2
Fp_1	Frontal Electrode
C3	Central Left Electrode
P3	Parietal Left Electrode
C4	Central Right Electrode
P4	Parietal Right Electrode
A1	Left Mastoid Electrode
A2	Right Mastoid Electrode
Cz	Central Reference Electrode
S1, S2	Stimulus
x	Signal Vector
E	Eigen Vector
g_1, g_2, g_3	Newton Phase

W_i	Row Vector
dB	Decibel
var	Variance
θmin	Average Correlation Time
X_x, X_y	Points of Trajectory in Space
$Xmin$	Minimum Value of Variable X
$Xmax$	Maximum Value of Variable X
Wi	Weight of the ith Item
¥	Dominance Matrix
$d^+ \& \ d^-$	Minimum and Maximum Distance from Hyperplane
$K(x_i, x_j)$	Gram Matrix

ABBREVIATIONS

ANOVA	Analysis of Variance
ApEn	Approximate Entropy
ANN	Artificial Neural Network
AR	Autoregressive
ARMA	Autoregressive Moving Average
BPNN	Back Propagation Neural Network
BSS	Blind Source Separation
BCI	Brain Computer Interface
CLT	Central Limit Theorem
CNS	Central Nervous System
CPU	Central Processing Unit
CO	Coherence
CCR	Correct Classification Rate
CD/CorrD	Correlation Dimension
CC	Cross Correlations
CS	Cumulative Score
DBI	Davies Bouldin Index
DNA	Deoxyribonucleic Acid
DFA	Discriminant Function Analysis
DZ	Dizygotic
DIC	Dominant Independent Components
ECG	Electrocardiogram
EEG	Electroencephalogram
EOG	Electrooculogram
ENN	Elman Neural Network
EER	Equal Error Rate
ED	Euclidean Distance
ERP	Event Related Potentials
FAE	False Acceptance Error
FAR	False Acceptance Rate
FRE	False Rejection Error
RR	False Rejection Rate
FFT	Fast Fourier Transform
FDR	Fisher Discriminant Ratio
FLD	Fisher Linear Discriminant
FastICA	Fixed point Independent Component Analysis
FT	Fourier Transform
f-MRI	Functional Magnetic Resonance Imaging

FA	Fuzzy ARTMAP
GBSP	Gamma Band Spectral Power
GMM	Gaussian Mixture Models
GA	Genetic Algorithm
GAR	Genuine Acceptance Rate
GAL	Grow and Learn network
HTER	Half Total Error Rate
HFD	Higuchi Fractal dimension
ICA	Independent Component Analysis
IR	Infra Red
ISI	Inter Stimulus Interval
*k*NN	*k*-Nearest Neighbor Neural Network
LGB-EEG	Late Gamma Band Electroencephalogram
LZC	Lempel Ziv Complexity
LDC	Linear Discriminant Classifier
LVQ	Linear Vector Quantizer
LV-EEG	Low Voltage Electroencephalogram
MEG	Magnetoencephalography
MD	Manhattan Distance
MPF	Median Power Frequency
MZ	Monozygotic
MLPBP	Multi Layer Perceptron Back Propagation
MUSIC	Multiple Signal Classification
MI	Mutual Information
NIRS	Near Infrared Spectroscopy
NN	Neural Network
NIM	Non-Invasive Methods
PET	Positron Emission Tomography
PSD	Power Spectral Density
PCA	Principal Component Analysis
Quad-SVM	Quadratic Support Vector Machine
RBFNN	Radial Basis Function Neural Network
RBF-SVM	Radial Basis Function Support Vector Machine
ROC	Rank Order Centroid
REM	Rapid Eye Movement
RSVP	Rapid Serial Visual Paradigm
RMS/Vrms	Root Mean Square
SNR	Signal to Noise Ratio
SFA	Simplified Fuzzy ARTMAP
SFAM	Simplified Fuzzy ARTMAP
SPECT	Single Photon Emission Computed Tomography
SEF	Spectral Edge Frequency

SpEn	Spectral Entropy
SRM	Structural Risk Minimization
SVM	Support Vector Machine
TAR	True Acceptance Rate
UR	Unrelated
VEP	Visual Evoked Potential
WPA	Wavelet Packet Analysis
WPD	Wavelet Packet Decomposition

CHAPTER 1

Introduction

1.1 Preamble

"Biometrics" is a Greek word derived from "Bio" (life) and "Metric" (measurement) (Drakos, 1998), i.e. the measurement of biological characteristics/personal traits. It is a Science dealing with identification/verification of persons based upon **physiological** and **behavioral** characteristics (Jain et al., 2011). The biometric systems are categorized into two classes based upon the traits of a person i.e. physiological (e.g. fingerprints, hand geometry etc.) and behavioral (e.g. signature dynamics, voice, keystroke etc.) (Jain et al., 2000), as shown in Figure 1.1. The physiological and behavioral characteristics both are distinct as well as measurable; hence, known as **identifiers**.

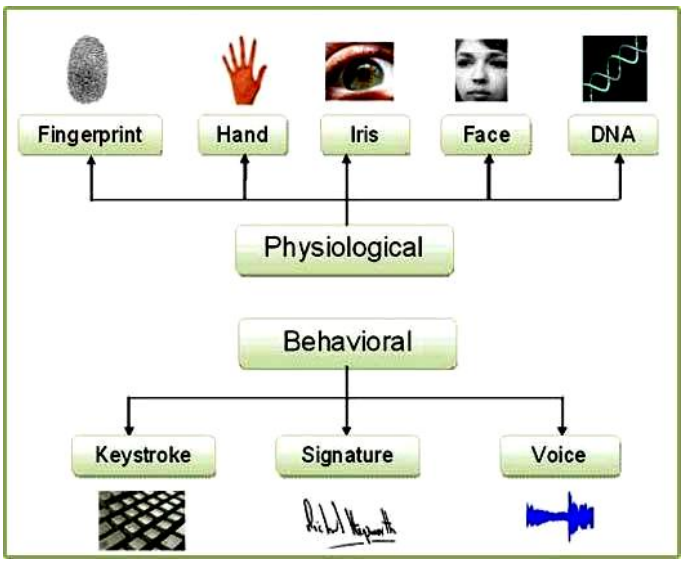

Fig 1.1 Physiological and Behavioural Biometrics
(Source: http://www.dynotech.com/articles/images/biometric-chart.jpg, DOA: 26-02-2016)

Two types of biometric system exist: Identification and Verification. The identification or verification is called **Authentication** (Goudelis et al., 2008). The authentication is done using following information (Wayman, 2009) as shown in Figure 1.2:

(i) Something you **know** (e.g. textual password): This is the most common authentication system e.g. textual passwords, numeric codes etc.

(ii) Something you **have** (e.g. smart card, Identity card or credit card with magnetic strip): These are the kind of objects possessed by a person for his/her authentication.

(iii) Something you **are (**e.g. fingerprint, iris, voice, ear, face etc.): These are the "built-in" features of a person distinguishing from others. These features are easily measurable and comparable.

(iv) Something you **do**: This denotes the roles performed by the users e.g. keystroke, signature etc.

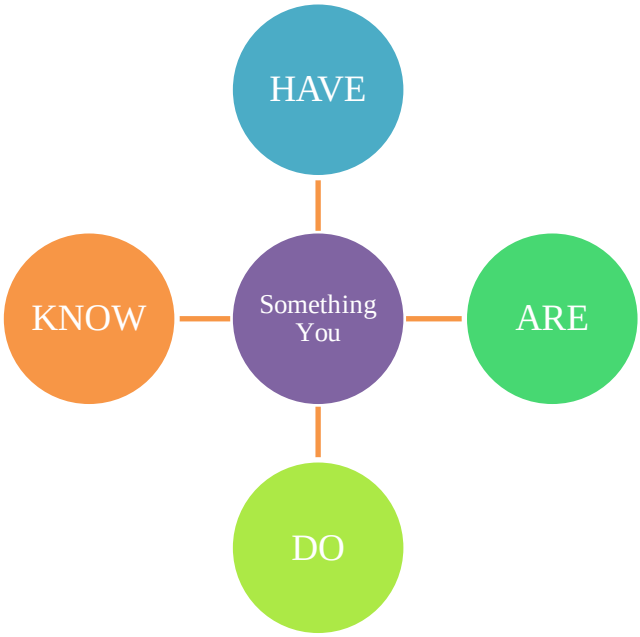

Fig. 1.2 Relationship between Authentication Classes (Wayman, 2009)

1.2 Types of a Biometric System

There are two major types of a biometric system i.e. **Identification** and **Verification**.

1.2.1 Identification: Here, the query biometric samples are matched with the stored database to authenticate or reject a person. It is a matching process of one-to-many (1: M) and nothing is known about a person before his/her identification. In fact, it is a *verification of linkage* between **known** (i.e. identifier) and **unknown** (Jain et al., 2007).

1.2.2 Verification: In verification, the query biometric sample of an individual is matched with an already stored database of the claimant. It is a matching process of one-to-one (1: 1) (Jain et al., 2007; Downes, 2005).

1.3 Characteristics of a Biometric System

The reasons for the use of physiological or behavioural characteristics of a human being for identification/verification is their specific characteristics like universality, uniqueness, permanence, collectability, performance, acceptability and circumvention (Jain et al., 2004).

- **Universality** is the specific characteristics that is universally possessed by every human being.
- **Uniqueness** is the distinction/differentiation between the characteristics of individuals.
- **Permanence** is the characteristics that remain invariant with time, position and condition.
- **Collectability** is the measurable characteristics.
- **Performance** means the accuracy and performance of the system.
- **Acceptability** is the acceptance of the system by the people.
- **Circumvention** means the fraudulent techniques applied to deceive the system.

1.4 Measurement of Performance/Error Rates

The performance of a biometric system is measured by its capability to authorize/reject a person belonging to the already stored templates in the database and is indicated by **Error Rates** (Ross et al., 2004).

Generally, two types of errors are made by a system.

- False Rejection Rate (**FRR**): Type 1 error.
- False Acceptance Rate (**FAR**): Type 2 error.

1.4.1 False Rejection Rate (FRR): FRR is caused when the legitimate user is rejected by the system (Ross et al., 2004). The rate at which the system *falsely rejects the claim of an authentic* user is known as False Rejection Rate.

1.4.2 False Acceptance Rate (FAR): The rate at which the system *falsely accepts an impostor* as a genuine user is False Acceptance Rate.

1.4.3 Equal Error Rate (EER): The point where FAR and FRR are equal is known as EER (Ross et al., 2004) and is an indicator of accuracy of a device, e.g. comparing two devices of the same manufacturer with EER of 1% and 5%, the device with 1% will be more accurate than the second one (Jain et al., 2007).

The relation between error rates and security threshold has been shown in Table 1.1, to understand the role of setting appropriate security threshold for person authorization/rejection. When, higher the threshold, FRR will be more and FAR will be less; and vice versa.

Table 1.1 Relationship between Error Rates and Security Threshold (Jain et al., 2011).

Security Threshold	**Error rates**	
	FRR	**FAR**
Higher	*More*	*Less*
Lower	*Less*	*More*

The use of high/low security threshold depends upon the purpose of the system e.g. lower security threshold is applied at amusement parks whereas, higher threshold at vital security places such as defense area or nuclear protected zone. Usually, these error rates are expressed as a percent of the total number of authorised/unauthorised attempts and are bound to a definite security threshold.

1.5 Conventional Biometric Systems

Broadly, the biometric systems are categorised into two categories based on *physiological characteristics* (e.g. fingerprints, facial recognition, palm print, hand geometry, iris etc.) and *behavioural characteristics* (e.g. typing rhythm, signature dynamics etc.) (Jain et al., 2006; Jain et al., 2011; Singla and Arora, 2010). Some of the common existing conventional biometric techniques are discussed as under:

1.5.1 Fingerprint Biometric

The patterns and geometry of fingerprints are different for different individuals which never changes with the growth of a person, even in case of twins (Jain et al., 2007). These patterns are hereditary and are formed before birth which remains as such throughout the life of a human being. The pattern of a fingerprint such as - *Whorls, Arches and Loops* along with patterns of R*idges, Furrows and Minutiae* are recorded for identification purposes (Ng et al., 2004). These patterns are processed and stored as an image or encoded computer algorithm for comparison. Such stored fingerprints are compared with that of query template for person identification/verification (Huvanandana et al., 2000). A typical image of a fingerprint is shown in Fig. 1.3, whereas, it's specific patterns in Figure 1.4.

Fig. 1.3 A Typical Fingerprint Pattern

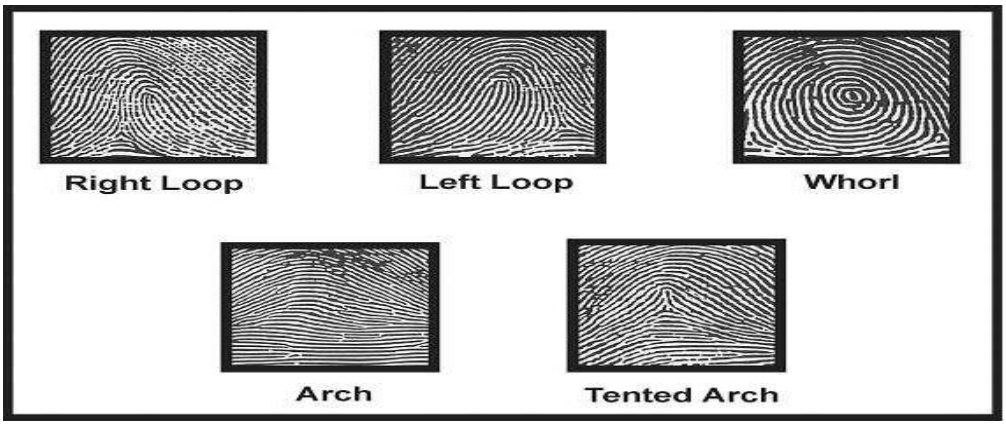

Fig. 1.4 Specific Patterns of a Fingerprint
(Source: http://www.ece.uah.edu/biometric/fingerprint_recognition.htm, DOA: 26-6-2014)

Fingerprints have unique and complex patterns such as Arches, Loops and Whorls. Their accurate patterns distinguish them from each other in terms of Archs, Bifurcation, Delta, Ellipse, Islands, Rods, Sweat Glands, Tented Arch, Spiral, Whorls (Chen et al., 2007).

However, fingerprint of a person can be spoofed by gummy finger. Similarly, amputees are not able to enroll for fingerprint scan etc. (Pankanti et al., 2002).

1.5.2 Voice Biometric

It is a combination of both behavioural and physiological characteristics of a human being (Reid, 2004). A human voice is generated within the appendages i.e. mouth, nasal cavity, lips, vocal tract. There may be some variation in the behavioral parts of voice because of age and medical condition etc. but physiological parts remain invariant (Soutar, 2002). Voice recognition is studied into two parts i.e. **speech recognition** (message coding/decoding) and **speaker recognition** (person identity verification) (Mason and Brand, 2002). This system is cheaper (due to low cost of the devices) and the acceptability of the system is high. However, voice of a person could be mimicked with various audio effects.

1.5.3 Hand Geometry Biometric

The pattern of Hand geometry is captured by standard optical camera or a scanner. Captured image of the hand is then converted into black and white silhouette (image contour), which remains unaffected by the environmental conditions like dust, sweat etc (Jain et al., 1999). In case of a 3-Dimensional (3D) image view, multiple cameras are employed with extra lights and mirror on sides to get the orthogonal view (Gonzalez et al. 2003; Jain et al., 1999). A typical hand geometry scanner has been shown in Figure 1.5.

Fig. 1.5 Hand Geometry Scanner System
(Source: http://www.hrindustries.co.uk/biometric-hand-geometry-reader.htm, DOA: 29-06-2014)

In order to construct template characteristics of a hand like length and width of a finger, angle between fingers, surface area, distance between the knuckles etc are recorded. (Reillo et al. 2000; Veldhuis et al. 2004). A picture of hand measurement is shown in Figure 1.6.

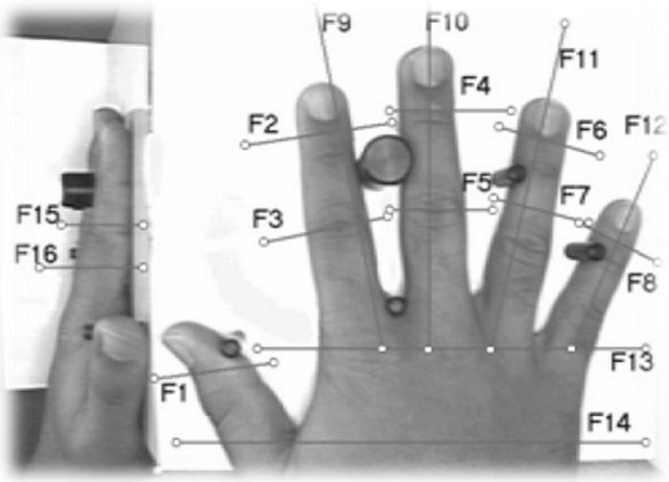

Fig. 1.6 Geometric Shape and Measurements of Hand (Singla, 2010)

For authentication purpose various methods are used like Euclidean Distance (ED) metrics, Principal Component Analysis (PCA), Correlation analysis for classification and comparison (Jain et al., 1999). However, hand geometry scanners require considerable size to employ and not fit for arthritic people because they are not able to place their hands on scanners properly (Jain et al, 2011).

1.5.4 Palm Print Biometric

Palm print and fingerprint shares the common background for authentication i.e. impressions of friction ridges (Figure 1.7). Normally, in a palm print, ridge patterns are studied i.e. flow of the ridges, features of ridges and details of the individual ridges (Kong et al., 2006). The palm prints features are matched on the basis of minutiae points (just like fingerprint), ridge matching and correlation points.

A variety of sensor/scanners (capacitive, optical, thermal etc.) are available in market to collect palm print image (Kong et al., 2006). However, large memory space is required to save palm print template. Moreover, dry or dirty hand obstructs the fissures of palm.

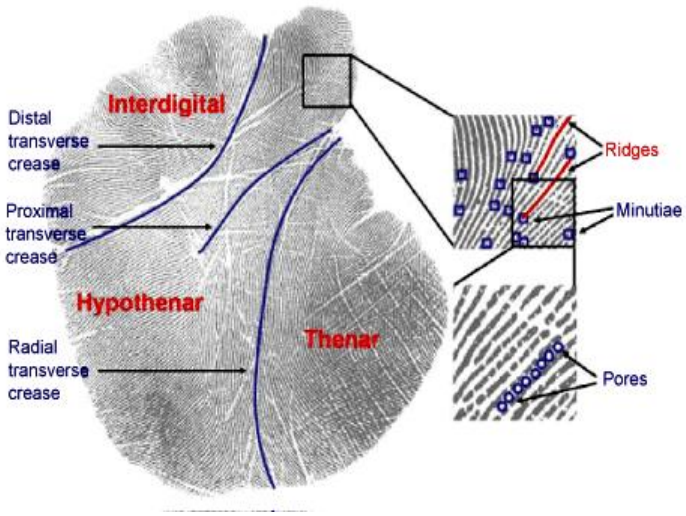

Fig. 1.7 Features of Palm Print
(Source: http://www.omicsonline.org/articles-images/2155-6180-3-150-g001.gif, DOA: 09-06-2016)

1.5.5 Face Biometric

The face biometric is based on connection between human face and the visual system. The most common method to extract features from face is *eigenfaces* method, which stores the images in a compressed format (Turk and Pentland, 1991). Such biometrics measure the key distances within the face i.e. eye, nose, mouth, angle between jaw, forehead etc. to form a template for matching as shown in Fig. 1.8 (Singla and Arora, 2007).

Fig. 1.8 Eigen Images for Facial Recognition (Deniz et al., 2003)

The face recognition system is very accurate and fast in processing. However, the recognition is affected by persons hair, lighting effect and spectacles worn person.

1.5.6 Iris Biometric

The pigmented part of the eye is called Iris and it is responsible for controlling the pupil size (Mitchell et al., 1998). It is an internal protected organ, which texture remains

stable throughout the life. They are immune to environment attacks and thus, considered as one of the prominent biometric system for individual authentication (Bowyer et al., 2008; Singla and Sethi, 2012). Iris forms a random texture within an individual. It is reported that even twins do not have the same iris pattern. Further, the individuals iris pattern differ for left and right eye (Jain et al., 2006). Various characteristics of an Iris are strips, furrows, crypts, coronas etc. (Figure 1.9). These are the vital points that are considered for template storage in biometrics (Wildes, 1997).

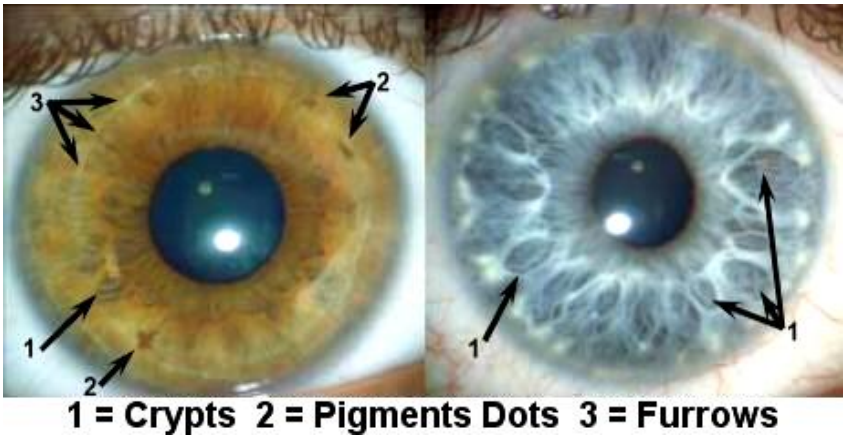

Fig. 1.9 Features of Iris
(Source: http://url4short.info/ea29777f, DOA: 29-06-2014)

Iris scan uses an infrared camera to capture high quality of iris structure. The captured images are converted into gray scale for iris code extraction on the basis of light and dark spots, followed by calculation of hamming distance between the two iris codes for person authentication process (Daugman, 2003). However, the iris scan is intrusive and a lot of memory is required to save the data (Evans et al., 2015).

1.5.7 Signature Biometric

It is based on dynamics of making a signature that involves pressure direction, acceleration, length of the strokes and duration (Guest, 2006). Devices such as digital tablets, two dimensional (2D) signature pads etc. are available in market to record and store signatures from hundreds/thousands of people with the help of special pens (Jain et al., 2004). The only disadvantage with such pads is the difference of signature pattern between digital and conventional signature over a paper. The signature verification is designed to identify person based on their unique writing style. However, a consistent user may find difficulty in submitting the identical signature pattern.

1.5.8 Vein/Vascular Pattern Biometric

Vascular pattern of a human being is used as biometric where, transmitted or reflected images of vessels are captured by exposing to near infrared device as shown in Figure 1.10 (Wang et al., 2008).

Fig. 1.10 Hand Vein Pattern using Infrared (IR) Camera
(Source: http://www.blogcdn.com/www.engadget.com/media/2006/02/Hand_vein2.jpg, DOA: 05-07-2014)

The reflected lights are captured by sensor placed beneath the hand in an image form. The characteristics like thickness and density of vessels, number of branches and angle between the branches are measured and stored as a template (Wang and Leedham, 2006). However, vein biometric has medium level of performance and acceptability (Evans et al., 2015).

1.6 Emerging Biometric Systems

The conventional biometrics suffer from various challenges e.g. the fingerprints can be spoofed with physical prints of fingers left on objects, iris pattern requires large storage space, faces are hindered with light effects, voice can be recorded and mimicked etc. (Roberts, 2007). In other words, the intruders can trespass to spoof the system. The fall in evaluation of conventional biometrics gives rise to new and emerging biometric modalities (Rodrigues et al., 2010; Singh and Singla, 2013). Some of the emerging/newer biometrics are discussed as follows:

1.6.1 Gait Biometric

In this system, the walking posture of a person is measured in a periodical fashion (Nixon et al., 2005; Nixon and Carter, 2006). It can be defined as "the coordinated cyclic combination of movements resulting in human locomotion" (Boyd and Little, 2005). Goudelis et al., 2008 categorised Gait recognitions in different oscillations i.e. shape, trajectory, pixel and self similarity. Figure 1.11 illustrates the measurement of some distance parameters like d_1, d_2, d_3 and d_4 (Cunado et al., 2003).

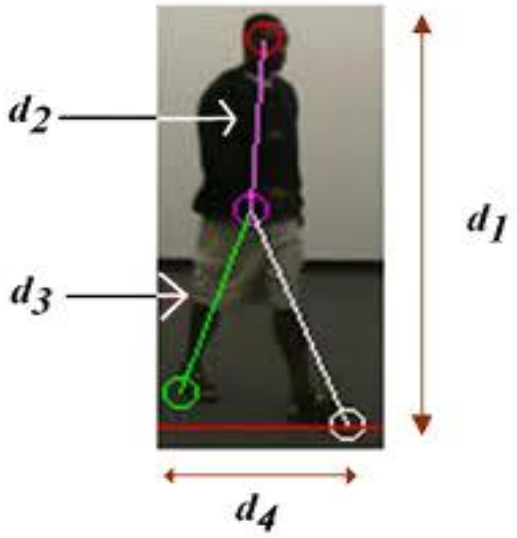

Fig. 1.11 Gait Biometric
(Source: http://fingerchip.pagesperso-orange.fr/biometrics/types/gait.htm, DOA: 27-06-2014)

The gait biometric requires a high resolution camera for motion detection. It supports a marker-less technique based on anthropometric proportions of human limbs and associated characteristics (Goffredo et al., 2008).

1.6.2 Thermogram Biometric

Every individual has a unique pattern of heat distribution generated by the vascular system of his/her face, which can be captured by infrared cameras (Goudelis et al., 2008). The captured images are matched with the one already stored as template with the help of Monte Carlo analysis for biometric recognition (Socolinsky et al., 2003). A typical example of the thermal image is shown Figure 1.12.

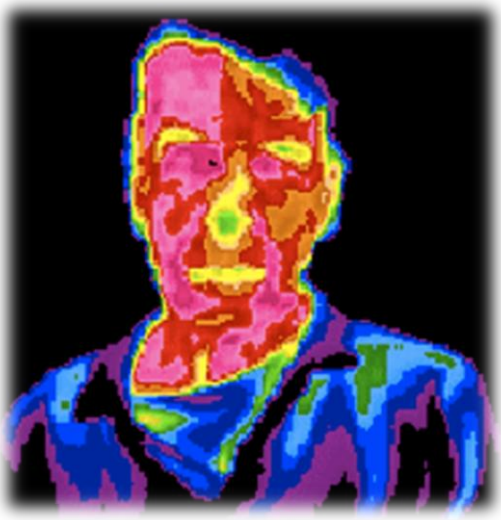

Fig. 1.12 Thermal Image of a Person
(Source: http://biometrics.pbworks.com/, DOA: 27-06-2014)

1.6.3 Smile Biometric

In smile biometric, a smile map is captured (due to muscle contraction beneath skin) with the help of a high pixel zoom camera (Guan et al., 2004). The way the skin changes its position (i.e. wrinkles), the associated motion vectors track the position and motion of the facial muscles. These tiny vectors and data points are stored in a template for authentication purpose.

1.6.4 Lip Biometric

Lip of a person deforms while pronouncing alphabets (especially vowels). During pronunciation the lip morphology is captured with a high definition camera (Omata and Hangai, 2001). An example of lip deformation is shown below (Figure 1.13) indicating changes in movement of lip while uttering vowels.

The shape vector due to structural deformation is compared with the reference one (during still images). Another approach of lip recognition is assisted by the shape and colour of the lip for person recognition (Choras, 2008).

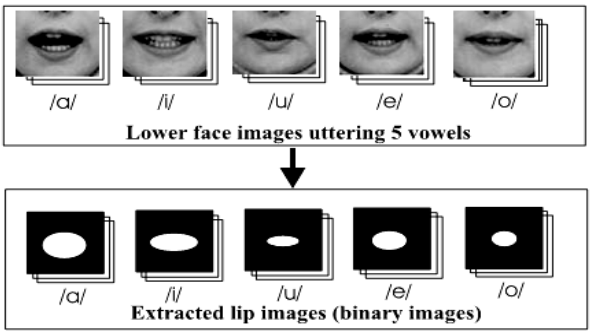

Fig. 1.13 Lip Image Deformations
(Source: Goudelis et al., 2008)

1.6.5 Body Odour Biometric

Body odour biometric is based on the analysis of olfactory properties of the body scent of a human being (Adeoye, 2010). It is a contactless biometric where, sensors (developed by University of Cambridge) are used to capture body scent from hand region (non-intrusive region) (Adeoye, 2010). The chemical/scent from an individual is stored as a template for biometric matching (Inbavalli and Nandhini, 2014).

1.6.6 Ear Pattern Biometric

Ear pattern may be more competitive and useful tool than the face biometric in future (Rowe, 2005). Like fingerprints and face recognition, outer ear pattern (pinna) has characteristic shapes like helix, antihelix, lobe, tragus, antitragus and concha as shown in Figure 1.14 (Pflung and Busch, 2012).

Features of ear are captured by clicking a picture or making a video or by pressing ear against a transparent firm material. Thereafter, the reference points are marked on the picture for metric purpose like median and tangent lines across the tragus, antihelix, lobule etc. (Figure 1.14) (Yan, 2006).

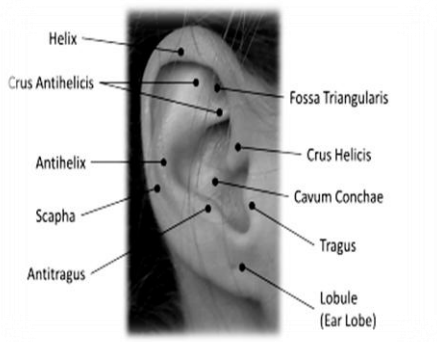

Fig. 1.14 Features of Human Ear (Pflung and Busch, 2012)

1.6.7 Electrocardiogram (ECG) Biometric

The Electrocardiogram (ECG) is the electrical activity of heart (Bronzino, 1995). The "*Fiducial points*" from the ECG are extracted from heart beat of a person and stored digitally as biometric template (Biel et al., 2001; Hoekema et al., 2001; Singla and Sharma, 2010).

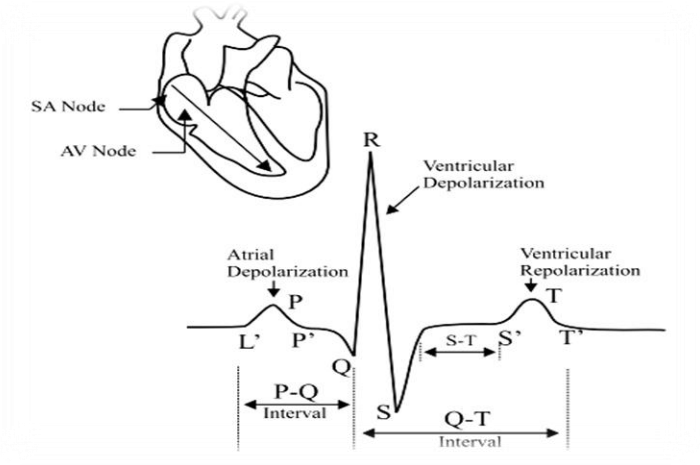

Fig. 1.15 Fiducial Points of ECG Trace (L', P', S' & T')
(Source: Goudelis et al., 2008)

In figure 1.15, points L, P, S and T marked with apostrophe (',) indicates **fiducial** points, where L' and P' denotes atrial depolarization while points S' and T' denotes ventricular repolarization. The literatures reveal that these points are unique for an individual (Biel et al., 2001) and is invariant with the state of mind, anxiety etc. Parametric processing techniques like correlation coefficient, wavelet distance measurement etc. are extracted from ECG signals to find the vital information for biometric feature set (Chan et al., 2006; Biel et al., 2001).

1.6.8 Electroencephalogram (EEG) Biometric

EEG is the electrical activity of brain, measured from the cortical surface of brain (Teplan, 2002; Bronzino, 1995). Very little research has been done on brain signals for biometric purpose. Initially, Poulos et al. (1998) and Paranjape et al. (2001) suggested that the brain-wave pattern of an individual is unique and can be used for personal authentication based on preliminary research by Vogel (Vogel, 1970).

The EEG signals are too noisy hence, processed first, followed by feature extraction and data classification (Paranjape et al., 2001; Poulos et al., 1999).

1.7 Comparison of Emerging Biometric Systems

A brief comparison of emerging biometrics has been shown in Table 1.2, along with their advantages and limitations.

Table 1.2 Comparison of Emerging Biometrics

Modality	Advantages	Limitations
Gait Biometric (Nixon et al., 2005)	Recognition possible at low resolution	Sensitive to type of clothes, illumination and movement
Thermogram Biometric (Socolinsky et al., 2003)	Person's heat signature	Temperature rise may affect the accuracy of the system
Smile Biometric (Guan et al., 2004)	Low cost device (camera)	Nerve disorder may cause wrong frame capture
Lip Biometric (Choras, 2008)	Prominent fissures lines like fingerprint.	Lip drowsiness or cracks produces error
Ear pattern Biometric (Pflung and Busch, 2012)	Easy to measure	Ear growth is not predictable
Electrocardiogram Biometric (Biel et al., 2001; Hoekema et al., 2001)	Unique to individual, liveliness detection	Common cardiac abnormalities
Electroencephalogram Biometric (Poulos et al., 1998; Paranjape et al., 2001)	Difficult to mimic, Liveliness detection	Noise is a big problem, difficult to process

The emerging biometrics have certain limitations e.g. like gait biometric is sensitive to type of clothes, thermogram biometric may get affected by temperature rise, nerve disorder causes wrong frame capture of smile biometric, lip biometric is sensitive to cracks and drowsiness, ECG get altered with major cardiac abnormalities.

The EEG is non-vulnerable to spoof attacks since, the biometric data is collected from the legitimate individuals. Only live persons are enrolled for recording EEG signals to measures the liveliness detection. Nowadays, smart EEG acquisition devices (Emotiv Epoch model) are available which can be applied to sensitive zones (military base, nuclear zone etc.) where human access need to be more secured. Thus, it is important to study EEG signal and its influence on different parts of brain, how they are correlated with mental attenuation and other exogenous (environmental factors) that is individual specific. The next section of this chapter deals with the thorough in depth study of EEG and its genesis.

1.8 The Genesis of Electroencephalography (EEG)

Electroencephalography (EEG) is the recording of the spontaneous electrical activity of brain over a short period of time. In other words, it is the recording of electrical activity of the brain along the scalp produced by the firing of neurons within the brain (Niedermeyer and Silva, 2004).

EEG is represented as measurement of *voltage* versus *time* (Sun, 2008; Paul et al., 2011). These are biosignals of low amplitude (μV) and low frequency (1-30 Hz), generated from a complex self-regulatory system and measured through changes in electric potential across a cell. The amplitude (measured from peak to peak) is the voltage of EEG, which varies from part to part of cortex i.e. 10-100 μV (Sanei and Chambers, 2007). The summated electrical signals from these cells represent the brain wave of a person (Buzsaki, 2006; Szathmary, 1999).

The electrical potential generated by a single neuron is too small to be picked up by EEG (Nunez and Srinivasan, 1981). The EEG always reflects the sum of the synchronous activity of millions of neurons, having similar spatial orientation, because there is fall off voltage field with square of distance (distance^2) and therefore, the electrical activity from the deep sources is more difficult to detect as compared to a current near the scalp (Klein and Thorne, 2007). Thus, thousands of post synaptic currents from a single neuron dendrite gets sum up to cause the neurons to generate **action potential** (Bronzino, 1995; Creutzfeldt et al., 1996; Nunez and Srinivasan, 1981). This neuron then synapses on other neuron and process continues.

The activity of brain can be recorded either by measuring the blood flow in the brain or measuring the electrical activity of neurons using invasive or non-invasive methods. **Invasive methods** refers to the surgical intervention (e.g. installing permanent electrodes in the brain) that causes serious risk (Hamalainen, 1993). **Non-Invasive Methods (NIM)** do not involve any physical damage to the brain and hence more useful for medical applications (Hamalainen, 1993). Some of the non-invasive methods are: Magneto-encephalography (MEG), Functional Magnetic Resonance Imaging (f-MRI), Near Infrared Spectroscopy (NIRS), Positron Emission Tomography (PET), Single Photon Emission Computed Tomography (SPECT), Electroencephalography (EEG) (Bronzino, 1995).

1.8.1 Frequency bands of EEG

EEGs are described in two terms: rhythmic activity and transients (Frackowiak, 2004). The rhythmic activities within a certain frequency are distributed over the scalp of biological significance. Mostly, the cerebral signals frequency are in the range of 1-30 Hz. Moreover, EEG signals are classified into five bands (Figure 1.16) as: (i) *Delta (δ)*: Up to 4 Hz; (ii) *Theta (θ)*: 4-8 Hz; (iii) *Alpha (α)*: 8-14 Hz; (iv) *Beta (β)*: 14-30 Hz and (v) *Gamma (γ)*: 30-100 Hz (Frackowiak, 2004; Bronzino, 1995; Bickford, 1987).

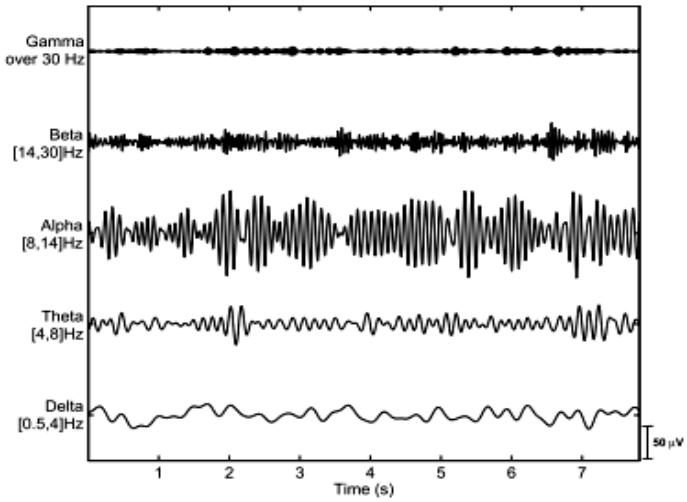

Fig 1.16 EEG Frequency Bands (Campisi and Rocca, 2014)

(i) **Delta (δ):** Delta waves are of low frequency (less than 4 Hz) and appears during epileptic seizures, un-consciousness and coma. These are generally seen in babies.

(ii) **Theta (θ):** Theta waves fall in the range of 4 to 8 Hz. It is normally seen in children or arousal in kids (Cahn and Polich, 2006).

(iii) **Alpha (α):** The range of alpha waves is 8-14 Hz and observed in the posterior part of head (both sides). These waves are reflection of relaxed state mental condition and originate from the occipital region (Niedermeyer and Silva, 2004).

(iv) **Beta (β):** Beta wave have frequency range of 14 to 30 Hz. These waves have symmetrical distribution and are evident in frontal region of brain (Stella and Treves, 2011). Beta activities are closely related to motor behaviour and they get attenuated during active movements (Li et al., 2011).

(v) **Gamma (γ):** These waves have frequency range of 30 to100 Hz and are of low amplitude (less than 2 µV). These are observed during Rapid Eye Movement (REM) and high consciousness (Cahn and Polich, 2006).

EEG signals are prone to artefacts which are classified into two classes: **physiologic** (originating from subject itself) and **extra-physiologic/technological** (artefacts arising from outside the body) (Niedermeyer and Silva, 2004). Thus, pre-processing helps to eliminate noises out of the EEG signals.

1.9 Genetic Factors influencing EEG Signals/Brain Activity

Brain activity is largely influenced by **genetic factors** as well as **non genetic factors** (i.e. **environmental factors**) (Vogel, 1970). The influence of these factors (genetic/environmental) on EEG characteristic were studied in intact families (especially in twins) and individuals. To comprehend the influence, *product-moment correlations* or *inter-class correlations* were examined on EEG to study the similarity/differences between twins, individuals and family members (Haggard, 1958; Varner et al., 1991; Poulos et al., 1998; Hazarika et al., 1997). The correlation factor for family members was calculated as ratio of covariance between family members to the total variance (Haggard, 1958), given by:

$$\textit{Correlation between the family members} = \frac{Covariance\ between\ family\ members}{Total\ variance} \qquad (1.1)$$

The correlation factor helps in determining the Heritability factor (h^2). The heritability factor for genetic variation is calculated as follows: (Falconer, 1981; Hume, 1973)

$$h^2 = 2 \times (\text{Correlation difference between individuals}) \qquad (1.2)$$

The individual *genetic information were contained within alpha (8-14 Hz) and beta rhythms (14 to 30 Hz) of EEG* (Vogel, 1958 and 1970). These two dominant frequencies were observed for most of the children and adults during awake condition (Andersen and Andersson, 1968). In unrelated persons, intra-individual variations were found in alpha rhythm of resting EEG and with phenotype model i.e. Low Voltage Electroencephalogram (LV-EEG) under standard condition over the course of time (Lennox et al., 1945; Anokhin et al., 1992; Davis and Davis, 1936; Raney, 1939; Nielsen and Harvald, 1958; Young et al., 1972). In addition to alpha domain, higher correlations were also observed for beta rhythm using band pass filters, revealing that *parietal and occipital region of brain carried the informative part of genetic influence* (Whitton et al. 1985; Meshkova and Shcherbo (1982).

The genetically determined differences are also related to behavioural and brain maturation with respect to Central Nervous System (CNS) functioning (assessed by neuro-

physiological techniques) (Dieker, 1967; Prakash and Chang, 1999; Vogel, 1958, Heuschert, 1963), which highlighted the preliminary findings on individual's EEG in relation to genetic association.

1.9.1 Spectral Analysis

The qualitative analysis of EEG is done by measuring its spectrum and expressed as *frequency* versus *square of voltage* (Salinsky et al., 1991; Dumermuth, 1968, Lykken et al., 1982). To understand the mental state differences between alcoholic subjects, Stassen et al. (1987) analyzed the spectral activity and found that a high degree of differences existed between twins and unrelated individuals (Stassen et al., 1988 a,b; Bouchard et al., 1990). Whitton et al. (1985) studied the spectral analysis with different frequencies and revealed higher differences between Monozygotic (MZ) twins and Unrelated (UR) persons. This study also supported the inclination of posterior region for genetic association.

1.9.2 Brain Activity at Different Arousal Levels

Significant difference(s) exist over EEG activity with different arousal levels i.e. (i) **During sleep**; (ii) **After ethanol intake** (effect of alcohol).

(i) **During Sleep**: Normally, a typical EEG pattern implicit five stages of sleep patterns (Rampil, 1998). It was found that MZ twins had similarity in their sleep patterns for all stages of sleep (Vogel, 1958; Zung and Wilson, 1967). A notable similarity in MZ twins and differences between unrelated individuals were observed for stages 2, 4 and Delta of sleep pattern (Linkowski et al., 1989; Merica and Gaillard, 1985).

(ii) **After Ethanol Intake (Effect of Alcohol):** An improvement in synchronization of EEG (especially in "Alpha" and "Theta" waves) was observed with ingestion of alcohol (Propping, 1977; Propping et al., 1981). There was a pattern difference over Alpha wave in reaction to alcohol and more dissimilar patterns between individuals.

1.9.3 EEG Variants

The rare EEG variants are: ***Alpha*** (Low Voltage EEG, Fast alpha EEG variant, monomorphic waves) and ***Beta variants*** (Vogel and Gotze, 1959). The variation in alpha

amplitude and alpha index was greatly contributed by genetic factors (Vogel, 1970; Lykken, 1982). The monomorphic waves (an Alpha rhythm EEG variants) were produced by exogenous factors inherited in Autosomal Dominant Mode (Dieker, 1967; Vogel and Gotze, 1959; Vogel, 1962; Vogel, 1966a; Kuhlo et al., 1969).

Vogel (1966 a,b) reported the mode of inheritance of 'β' variants, labelling that two 'β' variants shows Mendelian pattern of Autosomal dominance. In another study, the 'β' variants showed a model of multi-factorial inheritance (Vogel and Gotze, 1959; Vogel, 1970; Lykken, 1982; Steinlein et al., 1992). During brain maturation, a noteworthy chain was produced within 'β' variants which makes it genetically connected (Vogel, 1958; Courchesne, 1978; Thatcher et al., 1987; Heuschert, 1963).

1.9.4 Brain Activity and Event Related Potentials (ERP)

Event Related Potentials (ERP) is the recordings of neuro-electric activity against the responses of some external stimuli. The ERPs are explained in terms of polarity, latency time and topography. It is of two types i.e. **Exogenous** and **Endogenous** (Donchin et al., 1978). The *Exogenous* components (i.e. N100, P200) are evoked by external events; whereas, *Endogenous* components (i.e. N200, P300) by psychological events.

The variability can be observed in ERPs, recorded over different region of scalp with varying stimuli (Farwell and Donchin, 1988). ERPs reveal the genetic influence on functional neuro-physiological characteristics to a certain extent than anatomic features. In the *test-retest* reliabilities of ERP components, large individual differences were observed (Segalowitz and Barnes, 1993). There was a significant variation in reliability correlations (0.4-0.9 in case of P300; 0.4-0.8 for exogenous components; where, the reliability of auditory ERP was assessed with a factor of "r = 0.7") for 2 years of assessment (Segalowitz and Barnes, 1993). However, the reliability factor for exogenous components was low. Concluding the *heritability, the endogenous components have shown higher stability over exogenous components*.

The genetic influence of ERP components on twins, family members and group of individual's is summarized in Table 1.3 (Beijsterveldt and Boomsma, 1994).

Table 1.3 Relation between ERP and Genetic Analysis (Beijsterveldt and Boomsma, 1994)

Sr No	Author	Year	ERP Component	Methodology	Modality	Genetic Analysis
1	Dustman & Beck	1965	Waveform similarity Light flashes	Light flashes	Visual	Product-moment correlation
2	Osborne	1970	Waveform similarity Light flashes	Light flashes	Visual	Intra class correlation
3	Lewis et al.	1972	Waveform similarity	Clicks, Light and pulses	Visual, auditory, somato-sensory	Product-moment correlation
4	Young et al.	1972	Waveform similarity	Clicks		Product-moment correlation
5	Buchsbaum	1974	Auditory, visual augmenting/reducing response	Light flash	Auditory, visual	Intra class correlation
6	Rust	1975	P2 & P3, N2 & N3	Sound	Auditory	Genetic modeling
7	Geshon & Buchsbaum	1977	Augmenting/reducing response	Light flashes at different intensities	Visual	Intra class correlation
8	Surwillo	1980	P2 & P3, N2 & N3	Oddball	Auditory	Mann-Whimey U test
9	Malykh & Ravich-Scherbo	1986	Amplitude/latency motor related-brain potential (MRBP)	Reaction task		Intra class correlation
10	Kotcheibei	1987	Habituation amplitude/latency N 1, P2, N2, P3, N	Tones	Auditory	Genetic modelling
11	Polich & Burns	1987	Amplitude/latency P3 of infrequent tones	Oddball	Auditory	Product-moment correlation
12	Rogers & Deary	1991	Amplitude/latency P3 of infrequent tones	Oddball	Auditory	Intra class correlation
13	Bulayeva et al.	1993	Amplitude/latency of N60, P 1, N70	Reversing checkerboard	Visual	Correlation between offspring as well parents
14	o'Connor et al.	1994	Amplitude/latency of P3 of infrequent tones	Oddball	Auditory	Genetic modelling

*P2, P3, N2, N3 are various endogenous and exogenous stimuli types

The above data indicated a significant difference in brain activity when considering variable endogenous and exogenous ERP components, while the correlations were not affected by persons head length, width or position of electrode placement (Dustman and Bake, 1965).

1.10 Rationale of EEG as Biometric System

The present work is focused on Electroencephalogram (EEG) based biometric approach for human verification. These bio-signals are unique, confidential, secure, difficult to mimic and hard to be copied (Paranjape et al., 2001). In case of EEG, the identity of an individual is unlikely to be forged. The secrecy and privacy of the user is preserved. The biometric data is collected from the legitimate individual, who is practically present during enrolment. The EEG constitutes some specialties/characteristics which makes it a suitable candidate to be used as biometric, such as:

(i) *Universality*: Refers that every live individual must possess EEG signal.

(ii) *Liveliness detection*: Individual presence is must to produce biometric sample.

(iii) *Measurability*: It can be recorded using electrodes on specific organ of the body (i.e. along the scalp of human brain).

(iv) *Uniqueness*: These are genetically possessed and determined (Vogel, 1970). The reproduction of EEG is very difficult by another person (Niedermeyer and Silva, 1993).

(v) *Impossible to steal*: It is not at all possible to capture and mimic EEG signals from someone because it is a neo cortical biosignal (Vogel, 1970; Zhao et al., 2010).

The most important characteristic about EEG is that it detects changes over milliseconds (ms). An action potential needs only 0.5 to 130 ms to propagate across a single neuron depending upon the type of neuron (Frackowiak, 2004). In this way, EEG is faster, simple and practical as compared to other biometric systems. It is one of the emerging biometrics with low frequency one-dimensional data representation, whereas, anatomical biometrics (faces, fingers, hands, eyes, ears, voice etc.) have two-dimensional data representation (Evans et al., 2015). The comparison of the EEG biometric over existing conventional and emerging biometric is shown in Table 1.4.

Table 1.4 Comparison of EEG biometric with Existing Biometric Techniques

Existing Biometrics	**Limitations**	**Comparison of EEG biometric over existing techniques**
Fingerprint Biometric	Amputees would not be able to enroll	Amputees can be enrolled

Voice Biometric	Mimicking is easy with a trained person	No external sound effects required
Hand Geometry Biometric/Palm Print Biometric	Arthritic person, Shaking hand and tremors	Movement of head is restricted (Alzheimer's patients are exempted)
Face	Deceived using masks and spectacles	Masking is not possible for inbuilt neurons
Iris	Spoofed using colored lenses	Cannot be spoofed using external sources
Signature	Mastered with regular attempts	EEG wave patterns are not replicable
Gait Biometric	Posture affected by illumination and clothes worn	Clothes not required for brain mapping
Thermogram Biometric	Sensitive to temperature variation	Not sensitive to temperature variation
Smile Biometric	Nerve disorder changes smile reflexes	Nerve disorder affects recording
Ear Pattern Biometric	Ageing Effect	Neurons reduces with ageing effect
ECG Biometric	Large cases of cardiac abnormalities	Abnormalities cases yet to be examined

CHAPTER 2

Literature Survey

In this chapter, the main features of various methods to extract the data from EEG signals followed by the use of different classifiers for person identification/verification has been described.

2.1 Background

The preliminary study of EEG was done by Hans Berger in 1938 (Berger, 1938) in order to understand the concept of EEG inheritance and EEG variants. Based on concept of EEG specificity towards person identity, many researchers have tried to find the underlying information from EEG signals using various algorithmic approaches and machine learning algorithms as described in upcoming sections of this chapter.

2.2 Methods of Feature Extraction and Classification Techniques

The EEG based biometric has a better fraud resistant characteristics like *liveliness detection, uniqueness* etc. (Poulos et al., 2002). Since, the brain signals contain genetic information of individuals which are unique, confidential, secure, difficult to mimic and impossible to be forged and thus, beneficial in high security applications like Military services and combating terrorism. In this section, various methods of feature extraction from EEG signals, followed by the use of different classifiers for accurate and effective person identification/verification have been described.

2.2.1 Autoregressive Modelling of EEG signals

Autoregressive Modelling is a generalised form of Autoregressive Moving Average (ARMA) model in time series (Burg, 1968). The Autoregressive (AR) model forecasts the output based on previous output and input values. Thus, AR model represents the randomness of a process, describing the changes in signals as a function of time. A generalised form of AR model with "p" order is (Burg, 1968):

$$(X_t) = c + \sum_{i=1}^{p} \Psi_i X_{t-i} + \varepsilon_t \tag{2.1}$$

where, $\Psi_1 \ldots\ldots \Psi_p$ are AR parameters; c = Constant; ε_t = Noise.

Autoregressive modelling has shown significant results with brain activity. Poulos et al. (1999) studied parametric spectral analysis of EEG signals specifically on alpha rhythm for estimation of AR parameters from four different healthy individuals at rest with closed eyes. The EEG signals were analyzed and compared to a group of different individuals. It was fitted further with Neural Network (NN) Classifier i.e. Linear Vector Quantizer (LVQ) (Kim et al., 2011), indicating a classification rate of 72%-84%, supporting EEG specificity over genetic carrying capacity.

Paranjape et al. (2001) reported rigorous Autoregressive analysis in the range of order from 3-21 (Haykin, 1983), followed by classifier Discriminant Function Analysis (DFA) applied over the pool of 40 subjects to examine the degree of identity in the data pool, resulting in 80% classification rate.

Mohammadi et al. (2005) revealed the use of AR parameters with a competitive Neural Network classifier for person identification. The main features of their study constituted two different modes, one with simple AR features and the other with channel parameters to achieve accuracy in range of 80-100%. The recordings from the *parietal region* were more prominent with respect to other locations of the brain.

Palaniappan (2005) derived feature vectors from 04 subjects seated in dim light, noise free and sound controlled atmosphere while performing five different mental thoughts i.e. baseline, figure rotation, math task, letter composing task and visual counting task. The AR features from sixth order were extracted and were fitted to Linear Discriminant Classifier-LDC (linear classifier that classifies between two or more group of data) leading to 90% accuracy. The mental thoughts provided a comprehensive analysis when used in Brain Computer Interface (BCI) designs (Keirn and Aunon, 1990; Palaniappan et al., 2002a).

Marcel and Millan (2007) described “Gaussian Mixture Models” (GMM) and “Maximum A Posteriori Model Adaptation” technique for person authentication (or verification) from 9 subjects in 12 sessions over 3 days (4 sessions per day). The results were characterised in four protocols, examining the validation of algorithm on small and large dataset, followed by training and testing of data with incremental learning. In the study, an Half Total Error Rate (HTER) of 8.1-12.3% was observed for motor imagery task.

He and Wang (2010) reported person authentication based on Independent Component Analysis (ICA). The AR coefficients of these Dominant Independent

Components (DIC) were extracted, followed by employment of Naive Bayes probabilistic model resulting in HTER of 4.1%.

Brigham and Kumar (2010) developed the mechanism of imagined speech while recording EEG from 6 subjects uttering two different syllabi (/ba/ and /ku/). An Autoregressive features from 6 subjects were tested and classified for person identification using Support Vector Machine (SVM) with a correct classification score of 99.67%. A brief comparison of techniques employing AR modelling of EEG signals has been given in Table 2.1.

Table 2.1 Comparison of Methodology using Autoregressive Modelling of EEG Signal

Authors	Database	Condition	Methodology, (Feature extraction+ Classification)	Class. Accuracy	Advantages	Disadvantages
Poulos et al. (1999)	4	Eyes Closed	Autoregressive Modelling (α rhythm) + LVQ Neural Network	72-84%	Genetic influence on EEG's characteristics.	Validated on small dataset
Paranjape et al. (2001)	40	Eyes Open	Autoregressive Modelling + Discriminant Function Analysis (DFA)	49%-82%	Single electrode EEG recording made possible	Uniqueness was challenged with fluctuating results
Mohammadi et al. (2005)	10	Eyes Open	Autoregressive(AR) modelling + Competitive Neural Network	80% - 90%	Combination of AR parameters increases the accuracy	High order AR coeff. yield poor results
Palanniapan (2005)	4	Mental Task	Autoregressive (AR)- 6th order+ Linear Discriminant Classifier	90%	Mathematical activity shows maximum inter-subject variability	Long period study missing
Marcel and Millan, 2007	9	Motor imagery	AR , Power Spectral Density for GMM + Maximum A Posteriori model	HTER- 8%-12%	Left portion of brain produces more accurate results than right side of it.	Results are not certain because of small database

He and Wang, 2010	7	Motion Task	AR coefficient of Dominant Independent Component Analysis + Naïve Bayes Classifier	HTER-4.1%	Novel approach	Difficult to identify actual number of source signals and locations
Brigham and Kumar, 2010	126	Imagined speech and VEP	Autoregressive (AR) + Support Vector Machine (SVM)	99.76%	Imagined syllables tested as an external stimulus for better accuracy	-------

2.2.2 Visual Evoked Potential (VEP) and Gamma Band Spectral Power (GBSP) of EEG Signals

The VEP signals originates when a subject perceives visual stimuli (Niedermeyer and Silva, 1993). These signals are successfully used for classification of alcoholics and non-alcoholics (Palaniappan et al., 2002b). The gamma band frequency is related to memory related activities like visualising a picture (Basar et al., 1995; Basar et al., 1999; Bertrand et al., 1996; Bertrand et al., 1998). This makes it more specific to distinguish individuals because of different perception level.

Palaniappan and Raveendran (2002c) reported a new technique for individual identification using VEP signals and Fuzzy ARTMAP (FA) classification from 10 subjects (4 signals per subject) using 61 electrodes at a sampling rate of 256 Hz while the individuals were perceiving pictures, resulting in classification rate of 95%.

Palaniappan (2004) reported a method to identify individuals using VEP signals, selecting 20 subjects (40 trials per subject), thus a total of 800 VEP signals were recorded using 64 electrodes at a sampling rate of 256 Hz. In this study, the visual stimulus was given for 1 second at an interval of 5.1 seconds using the picture of Snodgrass and Vanderwart (1980) picture set, constituting pictures of easily recognisable items like ball, kite, banana etc. The pre-processing of EEG signals was done for removal of eye blinks (signals with magnitude above 100 μV were discarded) (Misulis, 1994). In this approach, a Back Propagation Neural Network (BPNN) was trained to identify individuals, achieving 99.06% classification for 400 test patterns. The results were validated using 10 fold cross validation scheme.

Palaniappan and Ravi (2006) made several modifications in their earlier studies and came out with multi-classifier system i.e. *Simplified Fuzzy ARTMAP (SFA), Linear Discriminant (LD) and k-Nearest Neighbour Neural Network (kNN)* applied over 800 VEP signals (Sharma et al., 2010). A strength of 20 subjects were involved in two sessions, one during eyes open state and other with eyes closed. The overall result was improved from 95% to 96.5% this time.

Palaniappan and Mandic (2007) studied in pursuance of their earlier studies (Palaniappan, 2004) with the perception that different persons have dissimilar activities against the stimuli or responses fed to them. The data were collected from 40 subjects in an RF shielded room (completely noise free) using 61 electrodes as per 10-20 International electrode system (sampling frequency: 256 Hz). The Snodgrass and Vanderwart pictures set was used as stimuli kept at 1 meter distance from the subjects. In this modified method, Davies Bouldin Index (DBI) was used for discriminating different channels. For classification, the Elman Neural Network (ENN) was employed resulting 98.56% recognition rate.

Das et al. (2009) reported the rapid visual categorization task while extracting the discriminative spatio-temporal filters for 0.5 seconds EEG epochs. Two classifiers: SVM and LDA were used for classification of identities. The performance of the system was evaluated in two phases (i.e. pre-stimulus and post stimulus) using SVM classifier achieving an accuracy of 94%.

Z´uquete et al. (2010) reported recording of 70 subjects VEPs with 8 occipital leads. The VEPs from gamma band were extracted and fed to a one-class classifier to target feature vectors using two modalities, namely *K-Nearest Neighbor* and *Support Vector* in order to produce the results in the form of True/False outputs with an accuracy of 90%.

Gamma Band Spectral Power (GBSP) is the estimation of power from the Gamma Band (30 Hz and above). It is usually recorded while subjects were subjected to Visual/Auditory stimulus either in external or internal form. Ravi et al. (2005) developed a novel method of biometric using Grow and Learn network (GAL) on VEP signals for person identification. In their study, VEP signals were processed first for elimination of eye blink artefacts. The study was made on 20 subjects using 61 channel electrode system for 800 VEP dataset. The GAL Neural Network has many advantages like high speed training and testing ability (Alpaydin, 1994; Olmez and Dokur, 2003). It is a new algorithm that describes an

association at one shot due to its incremental use as a local representation (Alpaydin, 1994). The study indicated an average classification rate of 85.09% using GAL network.

Ravi and Palaniappan (2006a) reported the use of Neural Network and Late Gamma Band EEG (LGB EEG, latency of more than 280 ms) features using 61 active electrodes. The features were classified by Multi Layer Perceptron Back Propagation (MLP-BP) Neural Network and Simplified Fuzzy ARTMAP Neural Network using a 10 fold cross validation scheme, resulting in an accuracy of 97. 33%. In order to lower computational time, design complexity and cost, Ravi et al. (2006b), designed an improved method for person identity, by including more subjects (40 instead of 20) in the study and reduced the number of required channels (27 channels instead of 61) by employing *Fisher Discriminant Ratio Function (FDR)*. When the numbers of channels were reduced, this method became less cumbersome and resulted in classification accuracy of 89.11 %. In this study, the classification improvement was small but with lower training and testing time as well as lower network size.

Yazdani et al. (2008) studied the feasibility of VEP for individual identification. In this study, the AR model parameters and Power Spectral Density (PSD) of the signals were extracted. Thereafter, the Fisher Linear Discriminant (FLD) was used for reduction of feature dimension followed by classification by k-Nearest Neighbour (*k*NN) method. At the end, the leave-one-out cross validation procedure was employed for validation of the proposed algorithm, achieving a classification accuracy of about 90% on a dataset of 20 subjects.

Palaniappan and Ravi (2006) made several improvements in their previous study, wherein GBSP of each channel was normalized by the total GBSP resulting in normalized vectors for correct classification 96.50% over the spectral band of all subjects. A comparison has been made in Table 2.2 between various approaches using VEP and GBSP.

Table 2.2 Comparison of Methodology using VEP and GBSP

Authors	**Database**	**Condition**	**Methodology, (Feature extraction+ Classification)**	**Class. Accuracy**	**Advantages**	**Disadvantages**
Palaniappan and Raveendran (2002c)	10	VEP	(VEP from Gamma band + Fuzzy ARTMAP	90.95%	A picture is used as stimulus (low cost)	Complexity increases with 61 recording electrodes

					architecture	
Palaniappan (2004)	20	VEP	VEP from Gamma band + MLP-BP Neural network	99%	Result has been found to be closer to 100%	More complex and time consuming
Palaniappan and Ravi, 2006	20	EYES CLOSED/ EYES OPEN	Norm. of GBSP by total GBSP + SFA, LD, *k*NN	96.5%	PCA improved the results with elimination of unwanted features	VEP over a long period lacks proper investigation
Palaniappan and Mandic (2007)	40	VEP	Visual stimulus + Neural Network	98.56±1.87%.	Davies Bouldin Index reduces the size and hence the complexity	Less number of subjects
Das et al. 2009	20	VEP	Spatio-temporal filter + Support Vector Machine and Linear Discriminant Analysis	94%	Post stimulus activity shows higher level of discrimination between subjects	Lower spatial resolution weakens the signal strength
Z´uquete et al., 2010	70	VEP	Visual Evoked Potential (VEP) from Gamma band+ *k*NN and Support Vector	90% and above	Personal classifier (authentication) based on only occipital leads	Single session study, lacking constancy
Ravi et al. (2005)	20	VEP Picture stimulus	Gamma band spectral power+ Grow and Learn (GAL) network	85.09%	GAL is fast and easy to train	Complex electrode architecture
Ravi and Palaniappan (2006a)	40	VEP Picture stimulus	Late Gamma Band EEG + Back-propagation and simplified fuzzy ARTMAP NN	97.33%	LGB-EEG are not time locked to stimuli	Complexity increases with higher number of electrodes

Ravi et al. (2006b)	40	VEP	Gamma band spectral power (GBSP) from VEP signals +Fisher Discriminant Ratio function	89.11%	PCA is used for noise reduction, pictue stimulus, low cost architecture	GBSP for a long period missing
Yazdani et al. 2008	20	VEP	Power Spectral Density (PSD) + Fisher Linear Discriminant (FLD), *k*NN	90%	Beneficial for cases where physiological and genetic tests has to be identified	Cumbersome and costly affair in comparison to fingerprint etc.

2.2.3 Multiparameter Feature Extraction

To make the system more reliable, robust and resistant against spoofing, multiple features were extracted from a single EEG recording. Instead of one feature, two or more than two features were extracted. Palaniappan (2006) extracted multiple parameter features like Autoregressive coefficients, channel spectral powers (alpha, beta and gamma), inter hemispheric channel spectral power and linear complexity (Palaniappan and Mandic, 2007b). Similarly, Riera et al. (2008), distinguished features like: (i) Single channel features e.g. AR parameters, Fourier Transform (FT) (ii) Two different channels (synchronicity features) e.g. Mutual Information (MI), Coherence (CO) and Cross Correlations (CC), representing joint characteristics of two channels. The multiple feature combinations imparted more qualitative and robust characteristics to biometrics.

Palaniappan and Paramesran (2002d) proposed a new technique using Genetic Algorithm (GA) and Fuzzy classifier, showing Discriminated mental differences in individuals with 96% accuracy. Palaniappan (2006b) reported individuals performing mental ability tasks, based on the cognitive analysis (which was different for different individuals). In this study, six electrodes were used instead of one electrode to acquire the EEG data from five subjects. Only 6 channels were used for data recording i.e. C3, C4, P3, P4, O1 and O2, defined by 10-20 Int'l system. Only 10 seconds was allotted for each mental ability task to be performed in 10 different sessions. Features like AR analysis, inter hemispheric differences from power spectra were classified by LDC. The Letter activity showed the maximum discrimination between the subjects with Minimum classification error of 1.36%, whereas, a combination of two activities i.e. baseline and letter, baseline and maths etc. the minimum classification error of 0.24% was observed with Maths and letter combination activity.

Further improvement was observed with more than 3 combinations of activities, resulting in zero percent classification error. In the context of Brain Computer Interface, Palaniappan (2006c) examined EEG signals during mental tasks and studied features like power and asymmetry ratios from delta, theta, alpha and beta bands.

Palaniappan and Mandic (2007b) designed a novel approach based on VEP signals. In their studies, EEG were recorded from 61 active channels placed according to 10-20 International electrode positioning system (sampled at 256 Hz). The duration of each picture was 300 ms (1 sec measurement) on 102 subjects. They proposed improved feature i.e Multiple Signal Classification Algorithm (MUSIC) dominant power technique using two classifiers namely ENN and *k*NN along with 10 fold cross validation classification. The MUSIC Algorithm (Akay, 1996) measured the power content of the EEG signals. The classification accuracy in case of ENN was 98.12±1.26; whereas, for *k*NN, it was 92.87 ± 1.49, 91.94 ± 1.54 and 96.13 ±1.03 (for k=1).

Riera et al. (2008), developed an unobtrusive method using only two frontal electrodes (FP1 and FP2) with reference to another one placed at the left earlobe. The basic goal of this study was to integrate the system with Enobio wireless unit (Ruffini et al. 2006, 2007), a dry electrode system. The data was recorded from 51 subjects (healthy human in the age group 20 to 45 years) and 36 subjects (intruders), keeping the recording condition similar for all the subjects (i.e. in relaxed state). This study indicated an True Acceptance Rate (TAR) of 96.% and FAR of 3.4 %. Palaniappan and Eswaran (2009) studied Simplified Fuzzy ARTMAP (SFAM) NN resulting in better classification score. Table 2.3 summarizes the results of multiparameter feature extraction and classification methodologies.

Table 2.3 Comparison of Multiparameter Feature Extraction Methods

Authors	Database	Condition	Methodology, (Feature extraction+ Classification)	Results (Clasf. Accuracy)	Advantages	Disadvantages
Palaniappan & Paramesran (2002d)	20	VEP	Genetic algorithm (GA) with Fuzzy ARTMAP (FA) + MLP-BP Neural network	96%	Discriminated mental differences in (37-50Hz) frequency range	Regions were localised and overlapped

Palaniappan (2006b)	5	Imagined activities	(Autoregressive coefficients, channel spectral powers (α, β and γ), inter hemispheric channel spectral power difference and linear complexity) + Linear Discriminant Classifier	95%	Mathematical activity has better accuracy	Complexity increases with higher number of electrodes
Palaniappan (2006c)	5	Imagined activities	Asymmetry ratios from EEG freq. range + Elman Neural Network	97.03%	Addition of gamma band for feature extraction increases the accuracy	Only few of the mental activity found to be significant
Palaniappan & Mandic (2007b)	102	VEP	Feature extraction (Multiple Signal Classification-Music) + (Elman Neural Network-ENN and *k*-Nearest neighbour Neural Network)	98.12±1.26%	Multiple Signal Classification (MUSIC) improves the accuracy	ENN is more complex to design and train
Riera et al. (2008)	51+36	Eyes Closed, relaxed state	AR modelling + Classification score	96.60%	Only 02 electrodes are used	EEG for a short duration is difficult to process
Palaniappan & Eswaran (2009)	40	VEP	Simplified fuzzy ARTMAP (SFAM) neural network + min–max clustering	96.67%	Executable in single simulation, found good with voting strategy	Limited only for presentation order

2.2.4 Oddball Paradigm for Biometric

Oddball paradigm is an integral part of Event Related Potentials (ERPs), where, stimuli (either audio or visual) are hidden in the repetitive sequence of common stimuli as rare occurrences (Polich and Margala, 1997). The subjects are asked to count or press a

button whenever they encounter such stimuli. An example of such stimuli is shown in Figure 2.1.

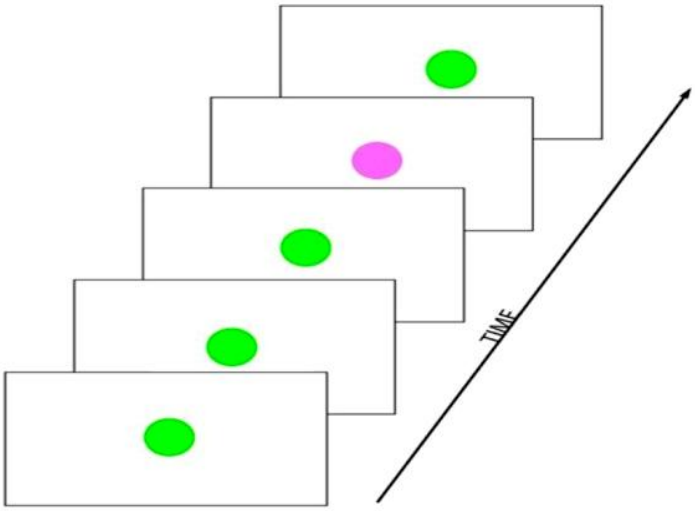

Fig. 2.1 Visual Representation of Oddball Paradigm (Gupta et al., 2008)

In Oddball paradigm, a positive peak near the parieto-central region of brain originates whenever a stimuli is given after 300 ms (P300 stimulus) where latencies of such stimuli may vary from 300-600ms (Polich and Margala, 1997). The amplitude and latencies of such targets differ depending upon the probability of occurrence of stimuli. In other words, VEP is an evoked response to visual stimuli while P300 is a component in VEP that is used in brain related study. It results when two stimuli are presented in probability manner in a random order. The *target* stimulus (occurring infrequently) is discriminated by the subject from the *standard* stimulus (occurring frequently) either by keeping a mental count or pressing the button (Gupta et al., 2008). In such conditions, the infrequent target stimulus elicits an evoked potential, characterized by P300 component (Sutton et al., 1967) with a peak latency of 300-600 ms for visual stimuli. This potential provides information about cognitive operations by reflecting the attention resource allocation in an engaged working memory.

Gupta et al. (2008) developed a technique for detection of a target in oddball paradigm (P300 paradigm). In their study, a novel Inblock paradigm was presented to enhance the evoked response of P300 component by analyzing the effect of targeted events against non-target blocks. On comparing techniques of both the paradigm, the results indicated that *energy analysis technique* had higher impact over *amplitude analysis* techniques. In this study, 04 young healthy subjects (3 males + 1 female) without

neurological or visual imparity were flashed two stimuli paradigm (*In block stimulus* and *Out of block stimulus*) on computer screen for a duration of 100 ms (Inter Stimulus Interval i.e. Inter Stimulus Interval-ISI of 750 ms). The EEG was recorded with 8 electrodes by placing them on standard positions along with mastoid electrodes (optimal location for P300 based system), using the extension of 10-20 Int'l electrode system (sampling rate 256 Hz). A break was given for each subject between two paradigms. A total of 200 recorded trials (60 trials of target + 140 trials of non target) were pre-processed and then analyzed. The recorded trials (P300 wave in 300-600 ms range) were averaged for 1 second each followed by calculation of Shannon energy (Choi and Jiang, 2008). The results indicated that Inblock paradigm was better than Outofblock paradigm, for all cases of features and for all subjects.

Touyama and Hirose (2008) used only one channel for EEG recording, while picture retrieving in oddball paradigm for person identification. Here, non targeted images were retrieved and examined along with common stimuli in 5 subjects, who were presented with nine photo images one after another in a sequential manner. To process the EEG data, Principal Component Analysis (PCA) was employed for feature alignment and reduction along with Linear Discriminant Analysis (LDA) classifier. A successful classification of 87.2 (5 time averaging) , 95.0 (10 time averaging) and 97.6% (20-time averaging) was obtained with target and non-target picture retrieval. This technique was very relevant for biometric application with lesser complexity (one channel recording) and less cumbersome task in data recording.

Gupta et al. (2009) reported an application level framework using Wavelet Packet Analysis (WPA) for improved target detection in oddball paradigm to establish the link between P300 components and the Gamma band in an Oddball Paradigm from a wavelet and neural viewpoint. In this study, all the parameters were kept as such as described earlier (Gupta et al., 2008), except the use of WPA and Radial Basis Function Neural Network (RBFNN) for oddball paradigm using only 40 trials. For target detection, the features were extracted from WPA analysis whereas, Daubechies (Db4) and Coiflet (Coif3) wavelets were used to extract the P300 and Gamma based energy features. The classification accuracy was compared when the P300 features were used with and without Gamma band features. Additionally, a new dynamic backward referencing technique was used as to enhance the features (Delta, Theta and gamma) from 08 channels. Finally, a radial basis function classifier was used to classify the features as target and non target for both the paradigm. About 78% overall accuracy was observed for Inblock stimulus with the P300 component (Delta and

Theta bands were used as feature vectors). This accuracy was increased to 85% when Gamma band energy was added as an additional feature. Similarly, an accuracy of 72% was observed for Outblock stimulus recordings, where Delta and Theta feature bands were used together. It was further increased to 77% when Gamma band feature was added, indicating that the novel paradigm might enhance the evoked responses during the visual task.

Gupta et al. (2012) exploited the usage of P300 paradigm for investigations in cognitive biometrics for person identification. In their study, four class oddball paradigms were projected to study the spatial location of stimuli in 8 subjects. The EEG was recorded using eight electrodes at a sampling rate of 256 Hz. In this study, oddball presentations were classified in three classes: Standard Oddball, Spatially Varying Oddball and Rapid Serial Visual Paradigm (RSVP). Alphabetical letters (A, B, C, D) were used for the paradigm design with Flash time of 100 ms and Inter Stimulus Interval of 750 ms. The Bayesian LDA was employed to get the classification results. The best performance among various paradigm (i.e. Standard Oddball, Spatial and RSVP) was observed with RSVP, where subject number 2 gained the maximum classification accuracy of 100%, advocating the ease of focusing on same spatial location.

Yang et al. (2011) studied an Event Related Potential (P300) while person receiving stimuli. The features were trained with Learning Vector Quantization (LVQ) NN for the classification of individuals to whom the P300 wave belongs. It was observed that the P300 wave was easier for the classifier to differentiate between diverse individuals as compared to other EEG signals. Additionally, they introduced a voting system into the identification process to improve the identification performance. After adopting the *voting* system, the ratios of correct identification of 92.14% was observed while *without voting* system, the average correct ratio was 63%, with an average of 76%. In their study, 451 trials from 7 subjects (60% of the trials randomly selected from each subject) was used to train the LVQ neural network with 8 hidden neuron and learning rate of 0.005. Overall, this study indicated that the P300 wave had a suitable input feature which was distinguishable and unique, and thus can be a potential tool in identification of person using P300 wave. Table 2.4 illustrates the brief comparison of study using oddball paradigm.

Table 2.4 Comparison of Oddball Paradigm Techniques

Authors	Database	Condition	Methodology, (Feature extraction+ Classification)	Results (Clasf. Accuracy)	Advantages	Disadvantages
Gupta et al. (2008)	4	P300 paradigm	P300 paradigms from visual stimulus + Neural Network classification	75%	Novel two way oddball paradigm introduced	Data collection found to be cumbersome
Touyama and Hirose (2008)	5	P300 paradigm	P300 paradigms + Linear Discriminant Analysis (LDA)	87.2 – 97.6%	One channel EEG recording	Small data set
Gupta et al. (2009)	4	P300 paradigm	P300 paradigms and gamma band analysis + Radial Basis Function (RBF) classifier	97%	In block and out of block paradigm results were greater with gamma band inclusion	VEP for gamma band has higher non-linearity
Yang et al. (2011)	7	P300 paradigm	Oddball paradigm (P300)+ LVQ Neural Network	92.14%	Voting scheme improves the performance	Results not found significant on large data pool
Gupta et al. (2012)	8	P300 paradigm	P300 oddball paradigms (3 structures) + Bayesian LDA	90%	Rapid Serial Visual Paradigm (RSVP) results are better	Ease of focussing on same spatial location alters results significantly within subjects

2.2.5 Spectral Analysis of EEG Signal

EEG signal are based on frequency bands of EEG signals where the whole spectrum is obtained by different mode of stimulus selection (Ahirwal and Londhe, 2012). The EEG data is cross-correlated followed by spectral matching and auto correlation in order to understand the specific genetic characteristic within the signal.

Poulos et al. (1998) studied the connection between genetic information and EEG of an individual. They extracted the information from EEG spectral analysis using Fast Fourier Transform (FFT) employing a computational geometry algorithm for identification of

individuals from alpha rhythm (7-12.5 Hz). The spectral analysis was done on convex hull (convex surrounding polygon in a 2 dimensional plane) from 04 subjects (sampling rate - 128 Hz). Procedurally, a convex polygonal structure of each individual was computed and was cross compared for any intersection between the same. 20 EEGs from all the four subjects plus 45 EEGs from other subjects (impostor) was matched for any intersection between the polygonal structures of the subjects. The study revealed classification score of 95%.

Poulos et al. (2001) explored the parametric and non-parametric technique spectral analysis. Thus, FFT from the EEG signals was calculated to understand the underlying behaviour change of EEG signal (Kehwar, 2005). A total of 4 subjects with 75 impostors were included in the study to form 4 groups (i.e. A, B, C, D). A neural network classifier-LVQ, was employed resulting in classification accuracy of 80-100%.

Poulos et al. (2002) reported the underlying information from EEG with non linear analysis of signal and its comparison with linear modelling. The EEGs were recorded with closed eyes for 3 minutes with a sampling rate of 128 Hz. A single session (3 mins) was segmented into six parts, thus producing 270 segments (6 x 45). A bilinear study was conducted with addition of extra non-linear component to AR model as to make it a general Bilinear Autoregressive Moving Average model. In this study, a Learning Vector Quantizer (LVQ) NN was employed for classification of subjects. The results were statistically significant when tested with chi-square test. There was a change in results, when EEGs were examined with bilinear feature extraction as compared to linear model i.e. classification score of 76-88% (bilinear) Vs 68-76% (linear model).

Ursulean and Lazar (2009) explored the spectral analysis of signal on the basis of cross-correlation properties of signal, while reducing the number of points for collection of EEG signal features (Huijnen and Eskes, 2012). In this study, a detrended cross correlation method was employed to examine the degree of correlation between the two points in a stationary time series under investigation (segmenting the series into small intervals to make the series stationary) (Podobnik and Stanley, 2008). The data was collected by Donchin paradigm (Farwell and Donchin, 1988) with a 6 x 6 matrix of characters to record the VEP signals. A total of 8000 samples were examined with an error of 5% or less.

Abdullah et al. (2010) reported a method when subjects rested with eyes open/eyes closed states. The subjects were asked to perform the tasks like: eyes open, eyes closed, imagining right index finger movement, imagining left leg movement and puzzle solving

(five sessions each). Four or less number of channels were employed for EEG recording. The feature vectors were constructed using Wavelet Packet Decomposition (WPD) (Ting et al., 2008) from four EEG rhythms. A Neural Network algorithm was employed for subject's classification. The results were insignificant, whether the subject's eyes were open or closed, achieving classification score of 81%. In case of 2 channel EEG recording, central region channels (i.e. C3 and C4) was preferred as it provided 71% classification accuracy, whereas the P4 channel was avoided in eyes open condition when 2 channels were used. A brief comparison between methods and results using spectral analysis has been tabulated under Table 2.5.

Table 2.5 Comparison of Methodology involving Spectral Analysis

Authors	Database	Condition	Methodology, (Feature extraction+ Classification)	Results (Clasf. Accuracy)	Advantages	Disadvantages
Poulos et al. (1998)	4 + 45 (Impostor)	Relaxed state	Computational Geometry Algorithms + Autoregressive Modelling (α rhythm)	95%	Individual's EEG classified using convex polygon technique	Results were preliminary and further investigation required
Poulos et al. (2001)	4+75	Rest with eyes closed	Spectral analysis (α,β) + LVQ Neural network	80-95%	Non-parametric processing results shows better accuracy	Results were not significant on large dataset
Poulos et al. (2002)	4	Rest with eyes closed	Non Linear modelling + LVQ Neural Network	60-80%	Bilinear model resulted in good classification	Complexity and computation increases
Ursulean (2009)	8000 test samples	VEP	Detrended cross-correlation algorithm + Neural Network	95%	Easy distinction, while drawing cross-correlation and anti-correlation map of EEG	Long range of EEG's cross-correlation is difficult to map
Abdullah et al. (2010)	10	Eyes ope/Eyes closed	Wavelet packet decomposition + Neural Network	81%	For 2 channel recording EO/EC does not affect the result	P4 channel distracts result in EO state

2.2.6 Time and Frequency Domain Analysis

The analysis in Time and Frequency domain is accomplished by examining the digitized signal with statistical change in voltage with time (Mishra and Singla, 2014). Time and Frequency analysis requires a strict statistical calculation for understanding the morphology and characteristics of EEG signal, based on probabilistic approach of random EEG signal. Recent works in Time and Frequency domain include the investigation of wavelet packet decomposition, entropy analysis etc.

Palaniappan (2008) computed AR coefficients, spectral powers, inter-hemispheric channel spectral power difference and linear complexity. In addition to this, they demonstrated non-linear complexity (approximate entropy) for two-stage authentication of individuals using the data of Keirn and Aunon mental thought activity from 5 subjects with cognitive analysis like: Baseline, Math, Geometric figure rotation, Letter composing and Visual counting (Keirn and Aunon, 1990). For classification, two threshold levels (Th_1 and Th_2) were used followed by computation of Manhattan Distance (MD) for each 50 training and testing data. The False Rejection Error (FRE) and False Acceptance Error (FAE) for 1000 EEG data was almost zero, except in individual no. 5 with FRE of 1.5% and FAE of 0.75%.

Abdullah et al. (2010) investigated WPD for analysis in Time and Frequency domain. The WPD analysis divides the signals into two components: low frequency component and high frequency component, resulting in signal decomposition into wavelet packet tree for inclusive signal analysis in different scales. The features were subjected to Neural Network classifier to attain correct classification score of 81% with 4 channel recording from Central and Parietal region of brain in relaxed state (open/closed eyes).

Mishra and Singla (2014) reported feature extraction from various Time and Frequency domain analysis of EEG signals for person verification. A total of 18 multi-features were extracted from 10 subjects at a sampling rate of 1000 Hz. Only two channels were selected i.e. Central and Parietal region of brain in relaxed state with eyes open without performing any task for 5 minutes each. The artefacts and eye blinks were visually inspected and removed for amplitudes above 100 μV. Various Time domain parameters (e.g. Root Mean Square, Average Frequency, Hjorth Parameters, and Lempel Ziv Complexity (LZ Complexity); Frequency domain parameters (e.g. Total Energy/Power, Band Powers, Median Power Frequency, Spectral Edge Frequency, Spectral Entropy) were computed for each

subject. The results indicated that the Hjorth parameter of Time domain and Spectral Edge frequency of Frequency domain had the minimum intra individuality and maximum inter individuality among a pool of 10 subjects.

2.2.7 Multi-Modal Biometric Fusion Techniques

Unimodal biometric employs a single biometric trait. In order to overcome the shortcomings of unimodal systems, a multi-modal system can be used for person authentication with more than one biometric trait (Ross and Jain, 2003). A Multimodal system is more robust as compared to unimodal system because of its higher vulnerability to spoofing attack, addresses the problem of non-universality and noisy.

The process of combining two or more than two biometric features is known as ***Fusion*** which can be achieved at sensor, feature, score and decision level (Riera et al., 2009). Features or scores from two different modalities are combined to form one feature. Here, some of the conventional and emerging biometric modalities have been compared which were fused for successful multi-biometric system (Table 2.6)

Table 2.6 Comparison of Biometric Traits and Fusion Techniques for Multi-Modal Architecture (Almahafzah andAlrwashdeh, 2012)

Modality	Level of Fusion	Fusion Strategies
Palmprint and Face (Kumar et al., 2009)	Matching Level	Sum of Score
Fingerprint and Hand-Geometry (Jain et al., 2005)	Combination Approach	Sum, Max, Min Scores
Face and Speech (Teoh et al., 2004)	Matching Level	Voting k- NN
Fingerprint, Palmprint, and Hand- Geometry (Anwar et al., 2009)	Feature Level	ANN
Speech, Signature, and Face (Stylianou et al., 2005)	Matching Level	Likelihoods Ratio
Audio and Visual Expert (Lipreading) (Ramli et al., 2008)	Decision Level	Optimal Weight (SVM)
Face and Fingerprint (Snelick et al., 2003)	Matching Level	Sum , Min-Max, and Zscore

Fingerprint and Face (Veeramachaneni et al., 2004)	Score and Decision	Sum Rule and Likelihoods
Face, Fingerprint, and Hand- Geometry (Ross and Govindarajanb, 2005)	Matching Level	Sum Rule

Riera et al. (2008) designed a wireless biometric system (Enobio), a 4 channel EEG signal recording system (developed at Starlab Barcelona SL), an easy, fast, compact and unobtrusive device for EEG recording. A total of 5 features (AR coefficient, FFT, Mutual Information, Coherence and Cross Correlation) were extracted from a 4 second EEG epochs. For classification, Fisher Discriminant Analysis (FDA) was employed for a group of 48 claimers, 350 impostors and 16 intruders (those who are not in the system). In this study, ECG and EEG signals were extracted and fused together for authentication of person with Equal Error rate of 0% for fused system. The use of only two electrodes was advocated with reference to the earlobe. The True Acceptance Rate (TAR) of 97.9% and FAR of 0.82% was observed when used with Linear binary decision method.

Liwen et al. (2010) reported the multi biometric modality using EEG and fingerprint for person identification. The fingerprint data was collected from 40 healthy volunteers (29 male + 11 female), from forefingers of right hand and seven images each. Fingerprint images were pre processed for proper orientation, segmentation, filtering, binarization and thinning and minute extraction. Thereafter, the extracted features were stored in a database as template for matching purpose (coarse matching, fusing and fine matching). A total of 480 EEG events were recorded from 40 individuals in two phases with a total of six sessions, one before the drink (i.e. water/coffee) and next 5 sessions after the drink. The feature set was constructed using AR coefficients (19th order) and Burg's Power Spectrum Density (PSD) followed by Naive Bayes classifier for person identification. The score level biometric fusion was achieved using Sum rule. The fused biometric has lesser Equal Error Rate of 1.12 in comparison to individual biometric modality EER (i.e. fingerprint: 2.71 and EEG : 4.16).

2.3 Observations from Literature Survey

After the extensive study of Literature, following observations are evident:

(i) EEG recording has always been a difficult task because of contamination from artefacts during recording. Some researchers have employed filters or consulted a physiological specialist for artefacts removal by visual inspection. Newer techniques may be employed to get pure signal for analysis and more accurate results.

(ii) A large number of EEG recording channels were used (61-128), which makes the system complex, cumbersome and also time consuming. Simplified data acquisition systems with one or two channel EEG recording system may be employed to reduce the complexity.

(iii) There is an ample scope for investigation of new parameters/features that remains invariable during recording conditions, irrespective of the session duration, gap etc.

(iv) The environmental factors related to EEG cannot be ignored. Therefore, the performance of the system can be improved with multi-modal architecture i.e. fusion with other biometric modalities.

2.4 Objectives of the Thesis

Considering the above mentioned facts, the following objectives of the Ph.D. research entitled "Development of Biometric verification algorithm using Electroencephalogram (EEG)" has been planned.

(i) To generate the data base of EEG samples.

(ii) To identify the unique parameter (s)/features for stable EEG biometric system.

(iii) To develop the algorithm for EEG based verification with reference to stored data in the template.

(iv) To explore the possibility of combining the EEG biometric with other biometric technique for enhancing the accuracy, security and performance of the system.

CHAPTER 3

Pre-processing and Feature Extraction

This chapter describes the methodology of data acquisition, pre-processing and feature extraction from EEG signals. The pre-processing employs the elimination of noise/artefacts from signals) before feature extraction and authentication. The methodology of data acquisition, novel techniques for artefacts removal and features extraction using Linear techniques and Non Linear techniques have been discussed in this chapter.

3.1 EEG Signal Acquisition/Database

Three main factors such as subject type, mental state and the type of stimulus were taken into account for EEG database as explained below:

a) The first dataset has a total of 960 samples, acquired/recorded from 32 subjects in the **relaxed state** in three different sessions.
b) The second dataset involved 900 samples from 30 subjects in the **Alcoholic/controlled state**, which is a standard dataset available at Neurodynamics Laboratory, State University of New York Health Center, Brooklyn.
c) The third dataset comprised of 100 samples from 05 subjects performing **mental task** using 04 channels. This is also a standard dataset primarily acquired by Keirn and Aunon, 1990.

3.1.1 Acquisition of EEG Signals during Relaxed State

The EEG signals were recorded from 32 healthy male volunteers in the age of 23-27 years. The subjects were instructed to lie on a flat bed in a noise free room with eyes open in relaxed state. A three-channel data acquisition system using BIOPAC-MP 36 (Biopac Systems Inc., Biopac Hardware Manual, 2015) was employed for recording of EEG signals.

3.1.1.1 Experimental Setup (Data Acquisition System)

The EEG data acquired using Biopac Student Lab (BSL MP-36) system. The data acquisition system easily connects to Windows or Macintosh system using USB cable. The system comes with in-built universal bio-amplifiers for recording of heart, nerve, muscle,

brain etc. and capable of processing signal strength from microvolt range to large analog signal strength i.e. up to ±10 Volts. A software tool (MP-PRO) guides the on screen instructions and a detailed lab manual for performing various exercises of data acquisition. The BSL MP-36 system is shown in Figure 3.1.

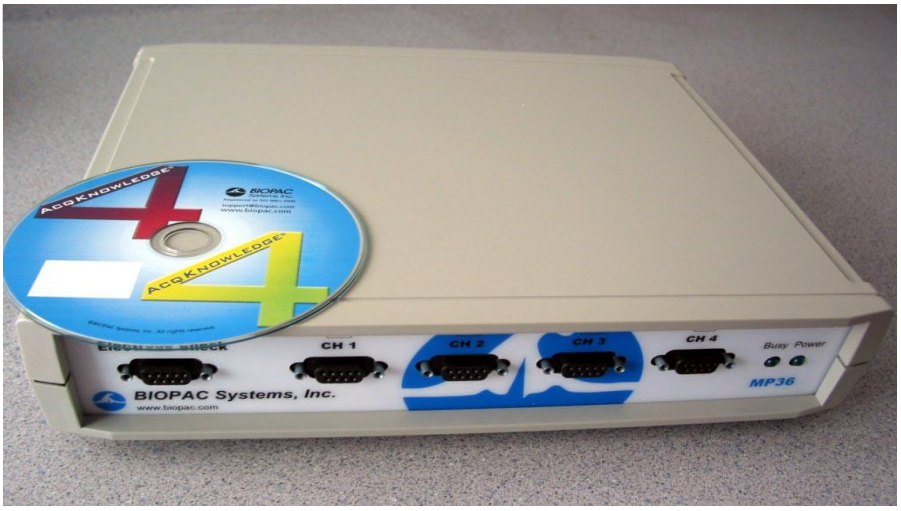

Fig 3.1 BSL MP-36 System

The common input devices are electrodes and transducers that connect to the front portion of MP UNIT that interfaces subject and the hardware. Input/output devices can also be connected to the MP UNIT. The systems front and back panel features are shown in Figure 3.2 and 3.3 respectively.

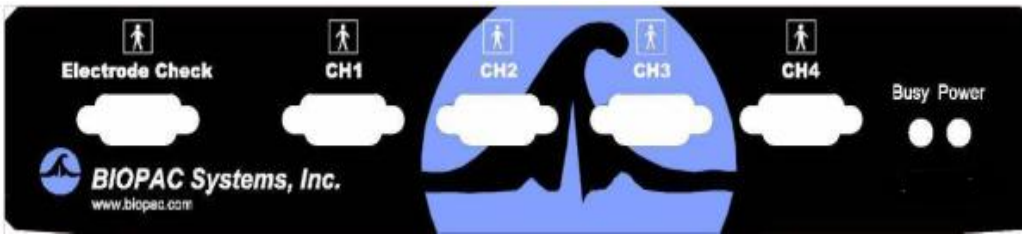

Fig 3.2 Front Panel of Biopac MP-36 Unit

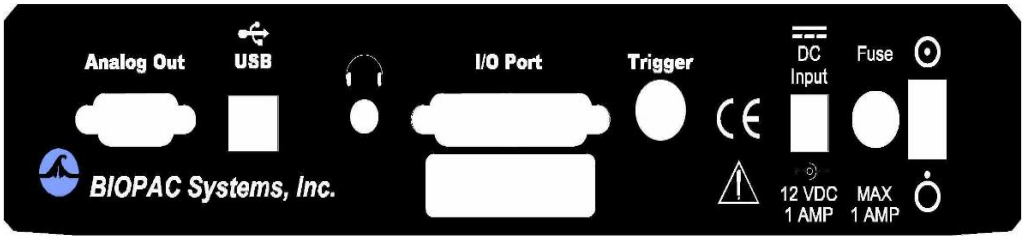

Fig 3.3 Back panel of Biopac MP-36 Unit

3.1.1.2 Electrode Leads of Biopac MP-36

The electrode acts as interface between skin (human scalp in our case) and MP acquisition system. The MP unit employs SS2L lead cables which adhere suitably to electrodes that connects to human skin and gives relatively accurate signal reading (as shown in Figure 3.4). The Leads I, II and III are standard bipolar electrode configurations. Each electrode is a small piece of conducting metal with a small diameter of 2.5 cm which is made up of polyvinyl material and can stick to one side (as shown in Figure 3.5). These are disposable electrodes filled with bluish gel that helps in electrical conductivity and flexibility to skin adherence.

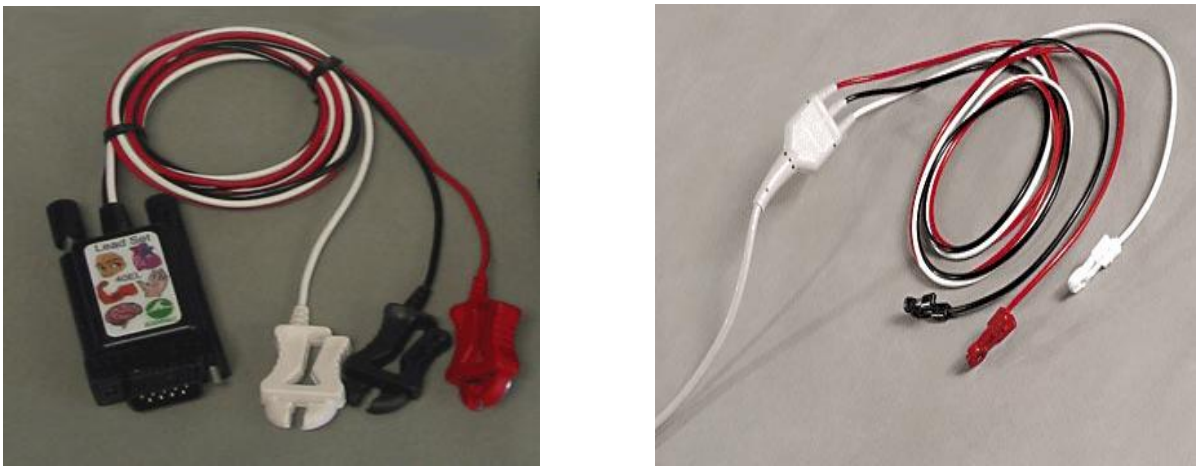

Fig 3.4 MP 36 Cable Leads (SS2L)

Fig 3.5 General Purpose Disposable Electrodes (EL-503 for MP 36 Unit)

3.1.1.3 Preparation and Connection of Electrode Site

In the first step abrading of skin site before electrodes are placed for proper conductivity was done. However, scalp skin is difficult to abrade hence this task was not performed. The electrodes were pasted at locations of less hair. To attach an electrode, they were peeled off from back and pressed forcedly on recording area.

Each electrode cable is of different color with code. The pinch connector acts as small clothespin which is polarized and clipped such that metal extensions within the clip are folded down to make proper surface contact with electrode.

It is advisable to place electrodes few minutes (5 minutes) before recording which establishes the proper contact with skin. The cable clip and electrodes placement is ensured properly. The subject is refrained from wearing any jewellery near the site and should not be in contact with nearby metal objects (faucets, pipes, etc.).

3.1.1.4 Software Setup

The first step is to set up the input channels for acquisition of data and relative parameters such as sample rate, data storage, and acquisition length.

(i) *Initialization* of the MP unit and its connectivity to computer was verified. For any improper connection between the system and computer, a warning message alarmed on software unit (BSL PRO Software). The Graphic User Interface (GUI) startup page is shown in Figure 3.6.

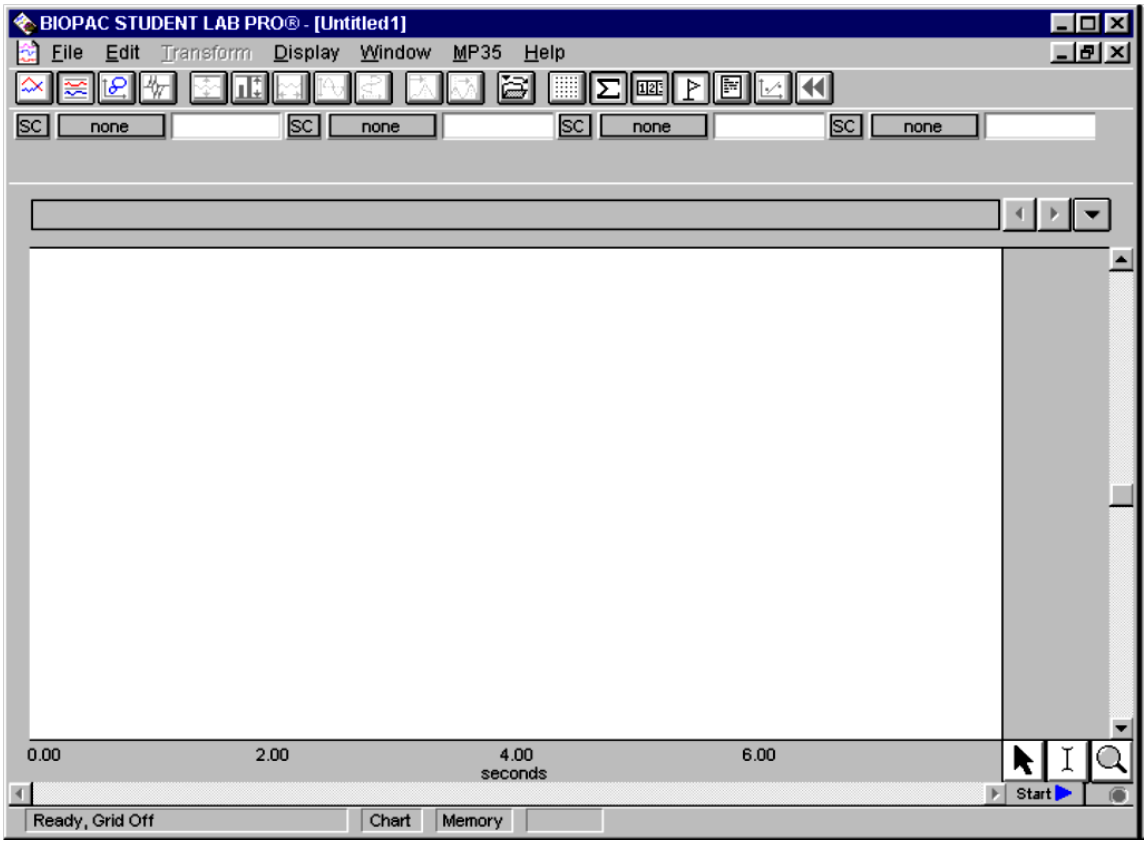

Fig 3.6 GUI Startup Page of BSL PRO Software

(ii) The second step involves the set up of *channel/acquisition setting*. This is achieved by deciding and selecting *Setup Acquisition* from dialog box of MP Unit. There are many options to avail however, basic operations were set like data storage folder (output), sample rate (1000 Hz) and acquisition length (4 second) (see Figure 3.7).

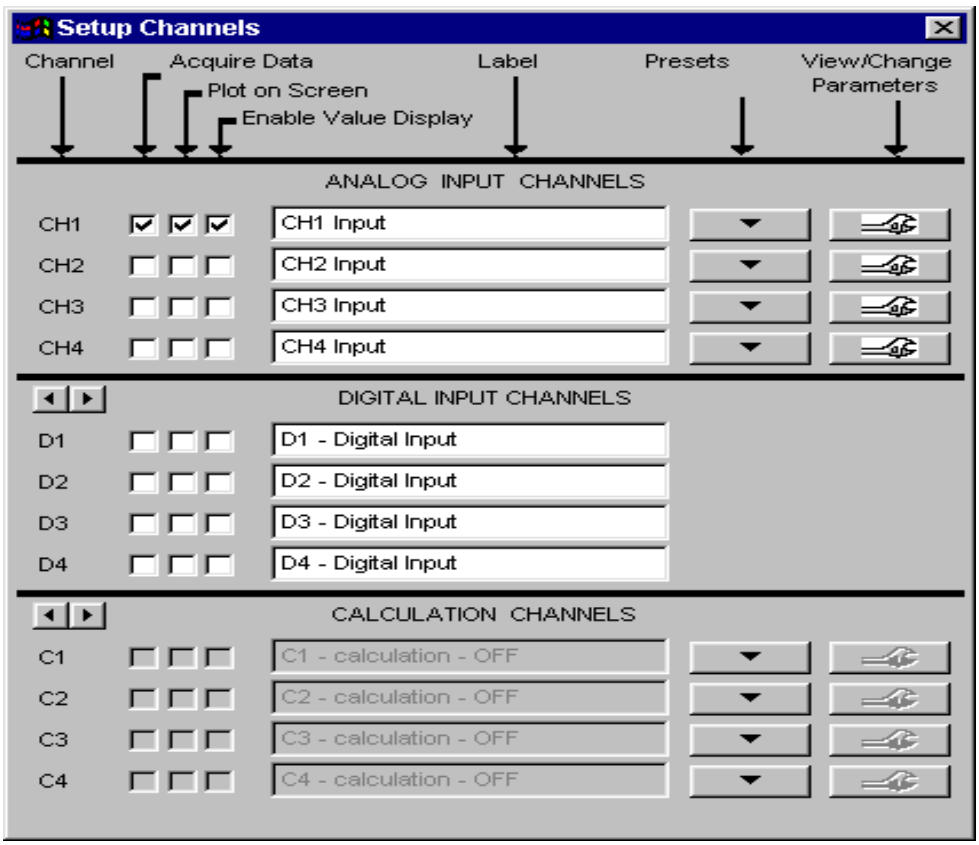

Fig 3.7 GUI for Channel Setup

(iii) *Signal Acquisition:* MP Unit can display multiple waveforms with one active waveform. The selected channel allows to highlight all or partial waveform and also enables transformations on a given channel.

(iv) *Filter operations:* The system employs two types of digital filters i.e. (a) Finite Impulse Response (FIR) which perform all post-acquisition filtering and (b) Infinite Impulse Response (IIR), that perform online calculations. The efficiency of IIR filters are more than FIR filters, thus they are used for online calculations. However, they tend to cause phase distortion. On the other hand, FIR filters are phase linear.

The IIR filters have a variable Q setting (defines the filter response), whereas, FIR lacks Q component. The default Q for an IIR filter was 0.707 (except for Band pass filters where Q

defaults to 1), with lower values resulting in a flatter response and higher values resulting in a more peaked response (see Figure 3.8).

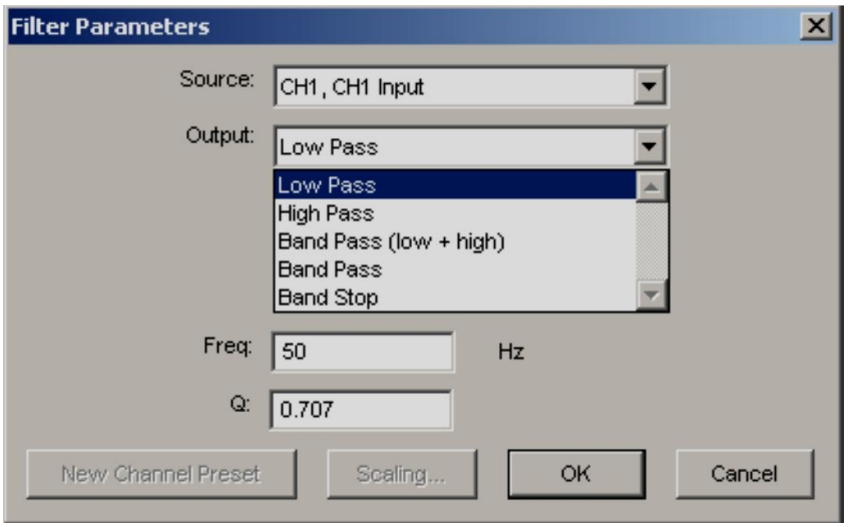

Fig 3.8 IIR Filter Software Setup

(v) *Equation Generator:* The MP system comes with equation generator that helps in solving various algorithmic approaches without any hassle or using any external software platform like Matlab or Labview. The Figure 3.9 shows the GUI for equation generator.

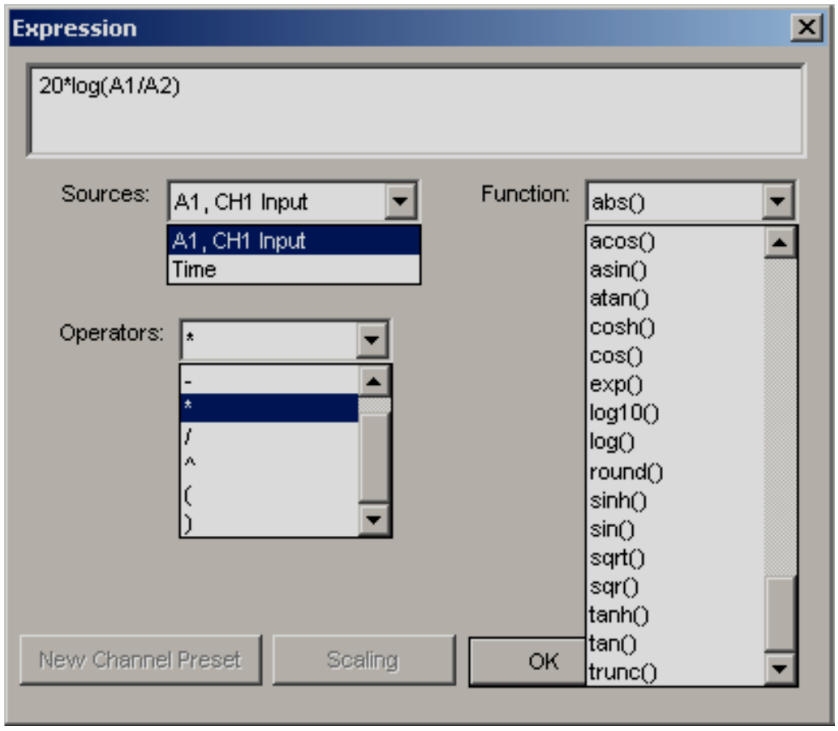

Fig 3.9 Equation Generator Software Setup

3.1.1.5 Channel Selection

The Central (C3) and Parietal (P3) channels have been selected because these regions have dominant alpha rhythm thus, inferring genetic disposition localised near the centero-parietal part of brain (Vogel, 1970; Anokhin et al., 1992). The electrodes were positioned as per 10-20 International electrode placement system using bipolar montage between Central (C3) and Parietal (P3) with the help of SS2L lead system of MP 36 Unit (regions marked shown in Figure 3.1) (Teplan, 2002; Homan et al., 1987). The central channel has been marked as yellow, parietal as green and reference as red (Fig 3.10).

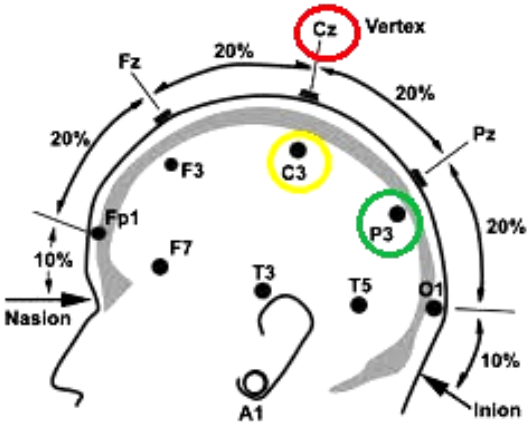

Fig 3.10 EEG Recording as per 10-20 International Electrode System (Teplan, 2002)

3.1.1.6 Recording Sessions

The EEG signals were recorded in three different sessions spread over three days. Each single session consisted of 10 trials with epoch length of 4 seconds each. Thus, a total of 960 samples (32 subjects × 30 trials) were captured at a sampling frequency of 1000 Hz.

3.1.2 EEG Dataset from Alcoholic/Controlled Disposition State

A total of 900 EEG samples from 30 subjects were availed as free source from the Neurodynamics Laboratory, State University of New York Health Center, Brooklyn (Lichman, 2013). The initial work included 122 subjects to study the genetic disposition on alcoholic and controlled state subjects (Ingber, 1997; Ingber 1998). The EEG signals were recorded with 64 electrodes as per 10-20 International electrode configurations at a sampling frequency of 256 Hz. The frontal electrode (Fp1 as active and Cz as reference) were selected because repetition tasks (visual stimuli of pictures in this case) caused higher reflectance on frontal lobe of brain (Olofsson and Polich, 2007).

The subjects were exposed with visual/picture stimuli either by single stimulus (S1) mode or dual stimulus mode (i.e. S1 and S2) for epoch length of one second each. The pictures were presented in two ways: *matched condition* (i.e. identical picture from S1 to S2 source) or *non-matched condition* (different picture from S1 and S2 source) to create a visual stimuli paradigm. The pictures for stimuli were selected from Snodgrass and Vanderwart picture set (Snodgrass and Vanderwart, 1980), as shown in Fig. 3.11. Every picture had approximate length and width of 5 × 10 cm wide. The gap between every picture stimuli was 300 ms. The answers were recorded by clicking computer mouse, when a similarity existed between matching condition of stimuli i.e. S1 and S2.

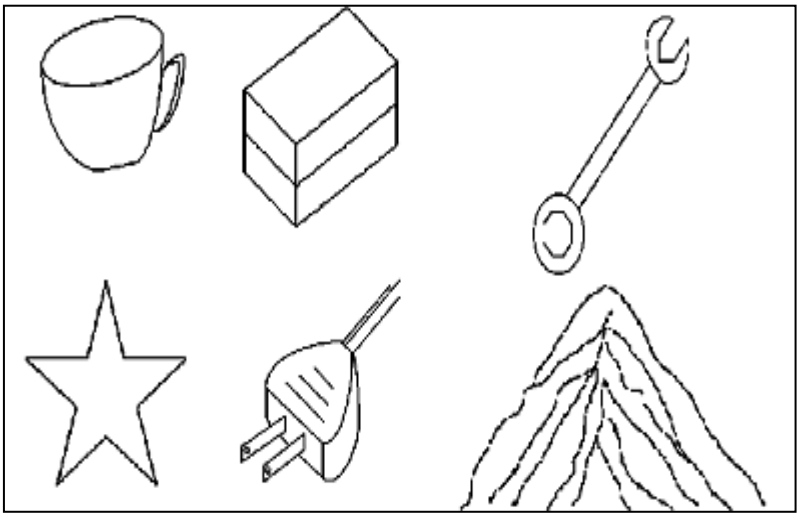

Fig. 3.11 Pictures from Snodgrass and Vanderwart Picture Data Set (Snodgrass and Vanderwart, 1980)

3.1.3 EEG Dataset from Mental/Cognitive Activities

It is a standard EEG database and available as free source from internet, primarily acquired by Keirn and Aunon to study the impact of communication between human and its surroundings (Keirn and Aunon, 1990). In this work, five subjects were selected in the age and dexterity as follows: Subject 1 (Age-48, Male, Left handed); Subject 2 (Age-39, Male, Right handed); and Subject 3 to 5 all were right handed male college students (Age 20-30).

Recordings were carried out using 10-20 International electrodes positioning system (Teplan, 2002) from positions C3, C4, P3, P4, keeping mastoids A1 and A2 as reference (Keirn and Aunon, 1990). The electrode placement is shown in Figure 3.12, where active channels are marked in orange colour circles. The EEG signals were recorded at a sampling frequency of 250 Hz for a short interval of 10 seconds and was repeated on different sessions.

All the electrodes were connected to a bank of Grass 7P511 amplifiers and bandpass analog filters set at 0.1-100 Hz.

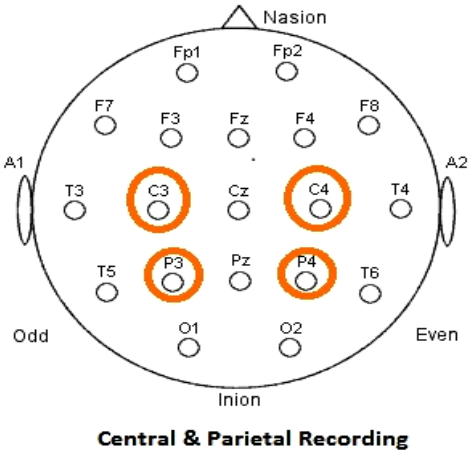

Fig. 3.12 Central and Parietal Channel Placement as per 10-20 Int'l Electrode System (Teplan, 2002)

The subjects were instructed to follow imagined activity/mental tasks as described below (Figure 3.13).

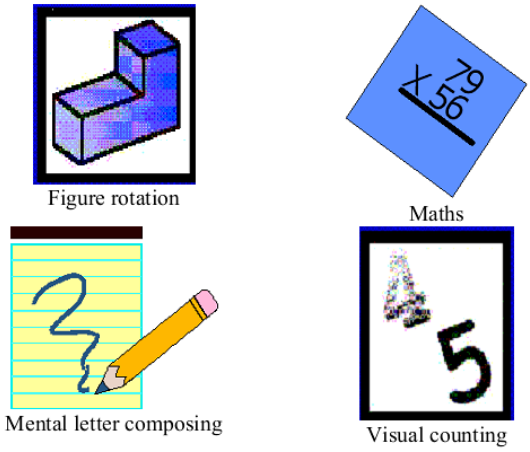

Fig 3.13 Pictorial Representation of Cognitive Task (Palaniappan, 2005)

(i) Baseline activity: In baseline activity, the subjects were instructed to relax their mind and abstain themselves from exercising any mental activity (Keirn and Aunon, 1990).

(ii) Counting activity: This was a visual counting activity where subjects were instructed to visualize a blackboard at which numbers were written in sequential pattern. The subjects were asked to remember the last number which was erased one after another (Keirn and Aunon, 1990).

(iii) Letter composing activity: The subjects were instructed to compose a letter in their mind without vocalising in detail (Keirn and Aunon, 1990).

(iv) Multiplication/Mathematical activity: In this activity, the subjects were assigned mathematical problems like multiplication of two numbers e.g. 54 multiplied by 78 etc. to solve in their mind without vocalising. The subjects were verified at the end of the task whether they concluded the solution of the problem or not?. It should be noted that none of the subjects completed the task before the end of their session i.e. 10 second (Keirn and Aunon, 1990).

(v) Geometric figure rotation: The subjects were asked to think of a 3 dimensional object rotated about its axis in rotational movement (Keirn and Aunon, 1990).

3.2 Pre-Processing: Artefacts and their Elimination from EEG Signals

The electrical signals originating from non cerebral region are called artefacts (Teplan, 2002). The amplitude of non-cerebral signals is quite larger as compared to the amplitude of the cortical signals (Alonso and Gil, 2012). They are broadly classified as: **physiologic artefacts** (originating from subject itself) and **extra-physiologic artefacts** (arising outside the body) (Alonso and Gil, 2012). Physiological artefacts are produced due to certain changes produced within the physiologic/body system or, due to some movement or change in reflexes of the body (Sethi et al., 2006). Some of the known physiological artefacts are: muscular (due to movement of muscles), pulse (because of presence of adjoining pulsating vessels), respiration (produced due to inhalation/exhalation) etc. On the other hand, extra-physiologic artefacts are produced due to certain changes shaped outside the physiologic/body system (Sethi et al., 2006). They are produced due to malfunctioning of electrodes, AC line noise (50 Hz), electromagnetic interference etc.

In this work, all the precautionary measures were taken to avoid such interferences. Thus, the system was calibrated, electrodes were tested, normal breathing was assured by the subject during recording of EEG signals. The EEG signals were acquired in a noise free controlled room. However, EEG signals susceptibility to eye blinks (EOG artefacts of higher amplitude of up to 100 μV) could not be stopped because study demands subjects to keep their eyes to be open. Blinking produces positive/negative spikes within the EEG signal. To counteract such problem, a novel method of Independent Component Analysis (ICA) has been employed.

The working of ICA can be explained with cocktail party problem where a mixture of sound (X_1 and X_2) is produced from a variety of sources (S_1, S_2 and S_3). The original sources (i.e. S_1, S_2 and S_3) can be retrieved back from mixed signal X_1 or X_2 with the application of ICA (Fig. 3.14).

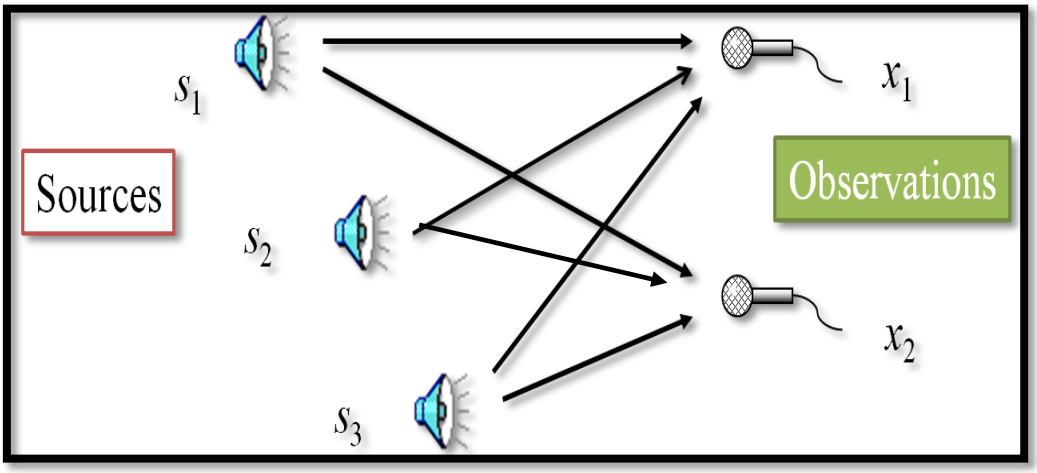

Fig. 3.14 Cocktail Party Illustration (Sound: x_1 and x_2) from Different Sources (S_1 to S_3)
(Source: http://52opencourse.com/?qa=blob&qa_blobid=2578963396071545839, DOA: 11-02-2016)

The detailed description of ICA and FastICA technique has been elaborated below.

3.2.1 Independent Component Analysis

The Independent Component Analysis (ICA) originated from the concept of Blind Source Separation (BSS) (Jung et al., 2000). The ICA method finds the underlying components from mixture of signals (multivariate statistical data) which are both statistically independent and non-gaussian (Hyvarinen and Oja, 2000; Ungureanu et al. 2004; Krishnaveni et al. 2005). Here, statistically independent means knowing the value of one signal does not give information about other one; whereas, non-gaussian characteristic defines the signal kurtosis and independability (Hyvarinen and Oja, 2000).

Non-Gaussianity of a signal can be understood by the concept of Central Limit Theorem (CLT) (John, 1995). The CLT in probability theory explains that distribution of sum of independent random variables tends toward a Gaussian distribution under certain conditions (shown in Figure 3.15) (John, 1995).

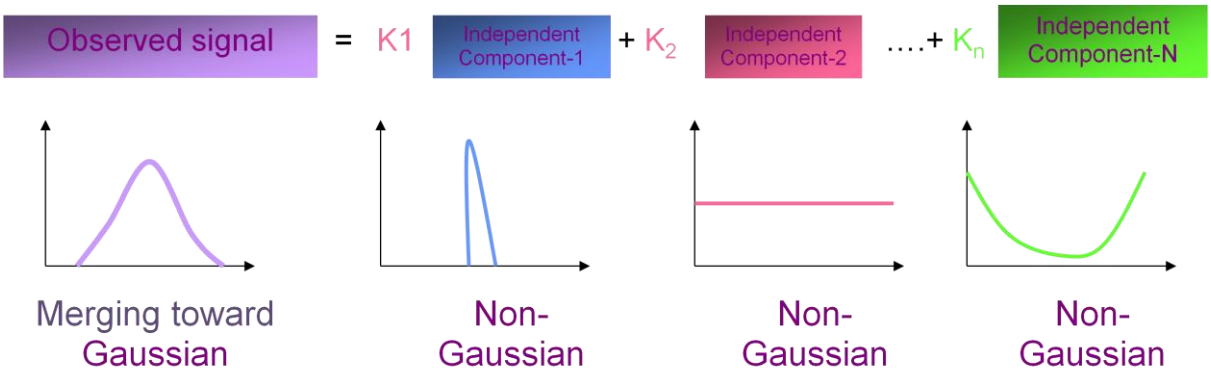

Fig. 3.15 Example of Central Limit Theorem (Nadine and Clementine, 2010)

3.2.1.1 Pre-processing by ICA

In ICA, signal is pre-processed to standardize the data and can be done in two ways i.e. centering and whitening.

(i) **Centering**: Centering reduces the dimensionality of data and makes the model zero mean. The mathematical expression for centering is (Hyvarinen and Oja, 2000):

$$\hat{x} = x - \mathrm{E}(x) \tag{3.1}$$

Here, 'x' is the signal vector; E(x) is the mean vector of 'x'

(ii) **Whitening**: Whitening is another important pre-processing step where the data is transformed into a new vector which is uncorrelated and variance equals to unity (Hyvarinen, 1999; Hyvarinen and Oja, 2000). It reduces the number of parameters and hence the complexity. Mathematically, it is expressed as (Hyvarinen, 1999):

$$\mathrm{E}\ \{\hat{x}\hat{x}^{\mathrm{T}}\} = \mathrm{I} \tag{3.2}$$

Here, E is the orthogonal matrix of eigen vectors;

$\hat{x}\hat{x}^{\mathrm{T}}$ is the Eigen Value Decomposition (EVD) of vector 'x'.

3.2.1.2 ICA Algorithm

Once the signals are standardized, ICA generalized model is created for artefact prone signals. Assuming that, the mixed signal (i.e. signal + noise) is a mixture of "n" linear mixtures ($x_1, x_2, \ldots\ldots x_n$) of n independent components, denoted as (Hyvarinen and Oja, 2000):

$$X_j = A_{j1}S_1 + A_{j2}S_2 + \ldots\ldots\ldots\ldots + A_{jn}S_n \text{ , for all } j \tag{3.3}$$

In equation (3.3), ‘X_j’ is a random vectors whose elements are mixture $x_1, x_2, \ldots x_n$ and ‘S’ is the random vector whose components are $s_1, s_2, \ldots s_n$. The above equation model can be rewritten in generalized form as (Hyvarinen and Oja, 2000):

$$X = As \tag{3.4}$$

The equation (3.4) is called Independent Component Analysis or ICA model. It is solved with assumptions that components of ‘**S**’ are statistically independent. Independent components follow non-gaussian distribution and the mixing matrix ‘A’ is square. After estimating the matrix ‘A’, one can easily find its inverse transformation ‘I’ i.e.

$$A^{-1} = I \tag{3.5}$$

$$S = IX \tag{3.6}$$

From equation (3.6), we can calculate each independent component of ‘**S’** from the mixture of signals (Hyvarinen and Oja, 2000; Vigario et al., 2000).

3.2.1.3 FastICA Algorithm

FastICA is a generalised model of ICA which measures the non-gaussianity of independent components by estimating the Negentropy (Hyvarinen and Oja, 1997). Negentropy finds the degree of information from a random variable. The more “random” the variable is, higher will be its entropy (Hyvarinen, 1999). The FastICA implemented with the FastICA package on MATLAB (Propriety of Mathworks, 2009b).

To find out Independent Components from a series, the weights associated with **‘x’** are considered (i.e. W_1, W_2 ...W_n) as independent sources. The algorithm for iteration (Hyvarinen, 1999; Xu et al., 1997; Agrawal et al., 2008) in FastICA is as follows:

(i) Take an initial row vector W_i

(ii) Apply Newton phase:

$$W_i = E\{\hat{x} g(W_i^T \hat{x})\} - E\{g'(W_i^T \hat{x})\} W_i \tag{3.7}$$

Whereas, $g_1(y) = \tanh(a_1 y)$; $g_2(y) = y * e^{(-1/2y2)}$; $g_3(y) = 4y^3$ (3.8)

(iii) Normalization:

$$W_i = (W_i - \text{Mean}) / \text{Standard Deviation} \tag{3.9}$$

(iv) De-correlation:

$$W_i = W_i - \sum W_i^T W_j^2 \quad (3.10)$$

(v) Normalize again {Repeat step (iii)}

(vi) If $W^T(i) \times W(i-1)$ is not close enough to 1, let W_{i+1} ,and go back to step (ii) (3.11)

3.2.2 Application of ICA on EEG Signals

All the computations were made on MATLAB R2009b platform (Propriety of Mathworks laboratory) with FastICA package.

The EEG signal contaminated with eye blink artefacts is shown in Figure 3.16 (a) (black shaded region). Normally, such artefacts have higher amplitude above the normal EEG range indicating a positive or negative spike on closing or opening of eye lids (Babušiak and Mohylová, 2009; Jiang et al., 2007).

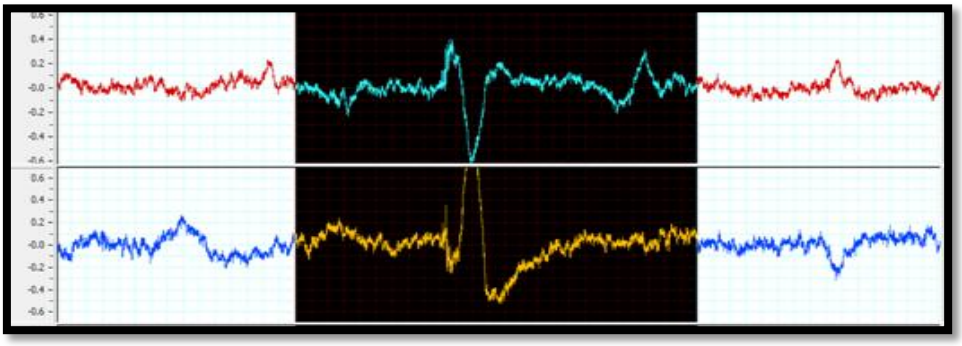

Fig. 3.16 (a) EEG Signal with Eye Blink

For remedial purpose, parallel EOG recording electrodes were placed near the eye lids of subjects. Figure 3.16 (b), shows the portion of signals (1000-1600 ms) with high amplitude due to eye-blinks.

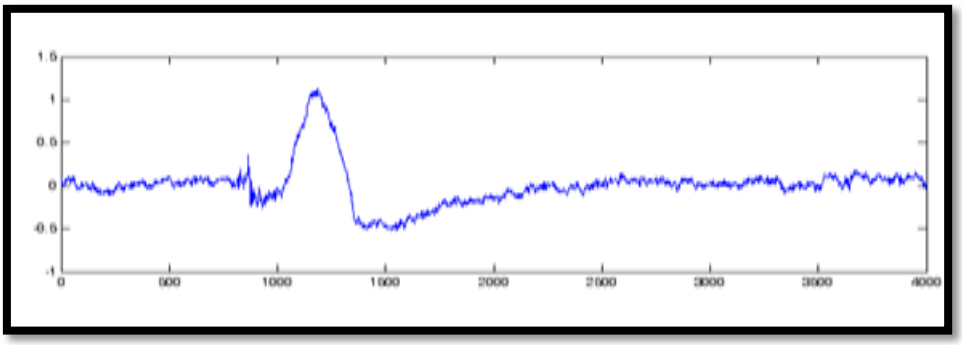

Fig. 3.16 (b) Portion of EEG Signal Contaminated with Eye Blink

The FastICA algorithm was applied over the mixed signals which lead to the separation of EEG and eye blink artefacts as shown in Figure 3.16 (c) and Figure 3.16 (d) respectively.

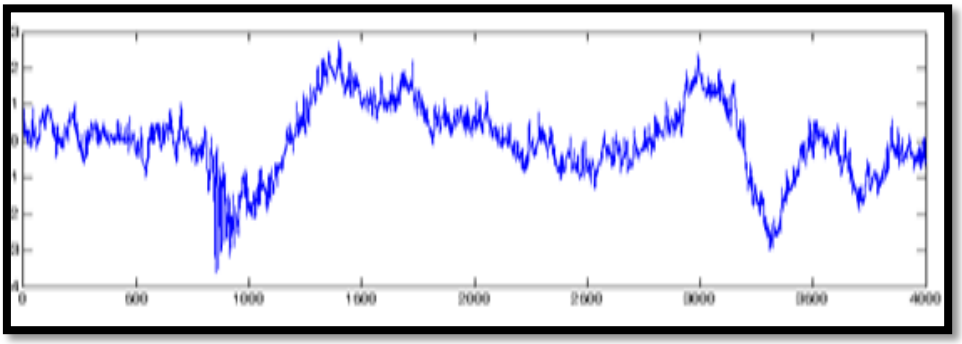

Fig. 3.16 (c) Artefact Free EEG Signal after FastICA Application

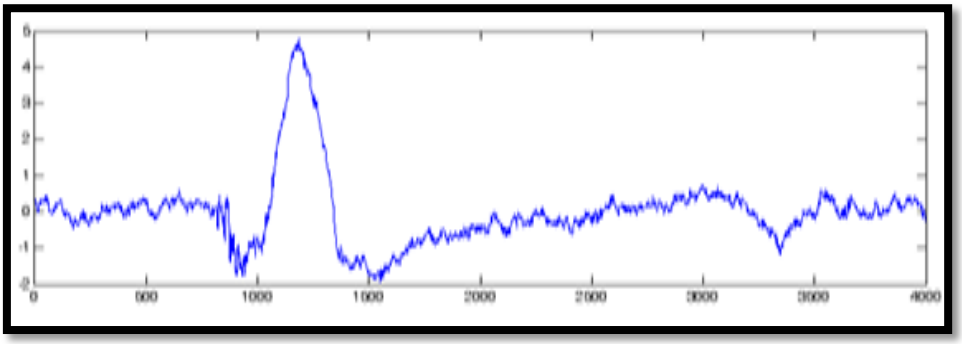

Fig. 3.16 (d) Eye Blink Artefact Separated out after FastICA Application

To detect the change or improvement in the signal condition, **Signal to Noise Ratio (SNR)** was calculated from pure signal after FastICA application. SNR is used to characterize the quality of the signal to the background or noise signal (Palaniappan, 2010). Mathematical SNR (in *dB*) is calculated as under (González and Woods, 2008):

$$SNR=20\ log_{10}\ (E_S/E_N) \tag{3.12}$$

where, Es is a average signal amplitude and En is average noise amplitude measured within the system bandwidth. In this case, the noise in non-linear and signal dependent where different calculations exists for different models.

The value of SNR for artefact prone EEG signals of 20 subjects is shown in Table 3.1.

Table 3.1 Improvement in SNR after ICA Iterations

SUBJECT_ ID	SNR (AFTER ICA ITERATIONS)
ID_01	2.5062
ID_02	4.4344
ID_03	4.1374
ID_04	5.1663
ID_05	5.4280
ID_06	4.6987
ID_07	5.0948
ID_08	4.6073
ID_09	5.8285
ID_10	5.9334
ID_11	6.1028
ID_12	5.1193
ID_13	4.6500
ID_14	5.2688
ID_15	4.8219
ID_16	4.5228
ID_17	5.6289
ID_18	5.0124
ID_19	5.4578
ID_20	4.2933

From Table 3.1, it was concluded that SNR has shown improvement indicating a change in signal rectification after ICA implementation.

3.3 Feature Extraction

After the removal of artefacts from EEG, the features were extracted from EEG for biometric matching. The proper selection of features is an important aspect for higher authentication. Here, Linear and Non-linear techniques of feature extraction have been employed. The Linear technique analyzes the features in **Time and frequency domain** whereas; Non-linear technique is based on fractal space i.e. **Fractal Dimension** and **Correlation dimension**. The non linear technique has been applied for analysis of inter

related cognitive tasks (dataset type-3) whereas, linear analysis applied on dataset type 1 and 2 i.e. Relaxed and Controlled disposition subjects.

3.3.1 Linear Features of EEG

The linear features were extracted in time and frequency domain. Time domain analysis was performed by examining the change in dynamics of EEG signal voltage with time (Hjorth, 1970). A number of statistical time domain features were extracted and analyzed from EEG dataset like: Root Mean Square (RMS/Vrms), Hjorth parameter, Approximate Entropy, Average Frequency and Lempel-Ziv complexity. Whereas, frequency domain features include: Total Power, Band powers, Delta ratio, BA ratio, Beta ratio, Median Power Frequency, Spectral Edge Frequency and Spectral entropy. A block diagram representation of time and frequency feature extraction is shown in Figure 3.17.

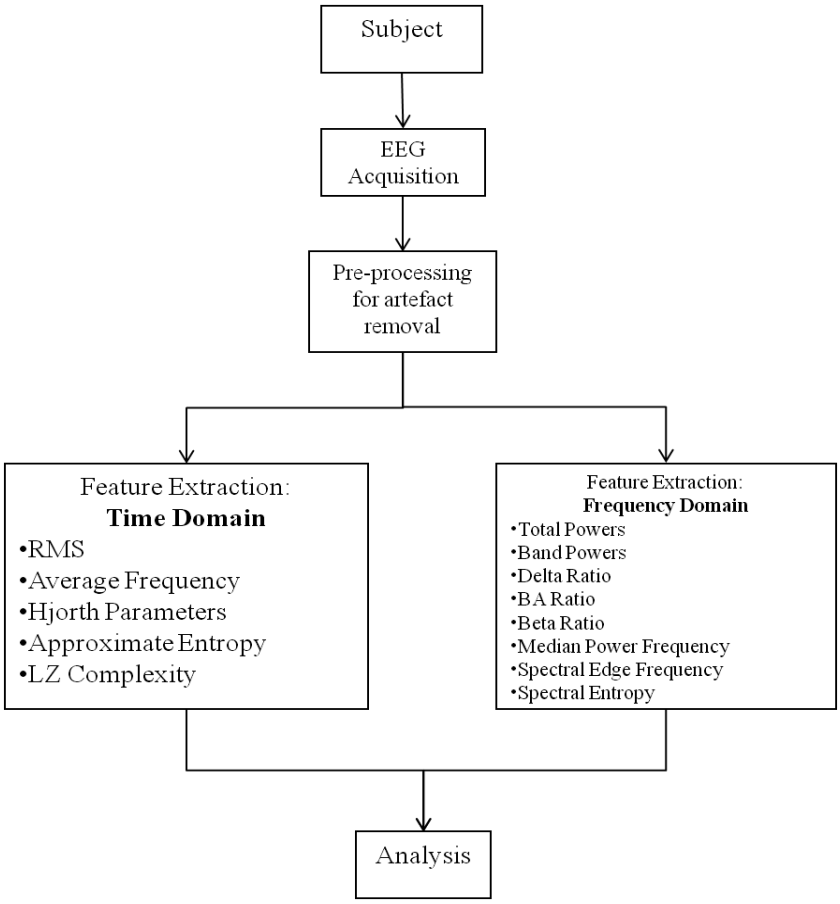

Fig. 3.17 Time and Frequency Feature Extraction from EEG Signals

3.3.1.1 Time Domain Features

The detailed description of the various time domain features is discussed below:

3.3.1.1.1 Root Mean Square (RMS/Vrms): The RMS measures the strength of a bio-signal (effective signal power) statistically, by measuring the magnitude of varying quantity from the motor cortical area (Basmajian and Deluca, 1985; Criswell, 2010). It compares the strength of signal by comparing their amplitude. Changes were observed in RMS with change in effect of stimulation or mental activity (Criswell, 2010). The RMS is calculated for values (x_1, x_2, x_3….,x_n) with 'N' number of observations as:

$$x_{rms} = \sqrt{\frac{1}{N}\sum_{i=1}^{n} x_i^2} = \sqrt{\frac{x_1^2+x_2^2+\cdots+x_N^2}{N}} \tag{3.13}$$

3.3.1.1.2 Average Frequency: Average frequency of a signal is defined as the number of zero crossings of the signals per second time (Burch, 1964; Rampil, 1998). Average frequency is somewhat difficult to measure because of presence of high frequency components in EEG signals. It is calculated as signal length 'X' as (Burch, 1964):

$$Signal(i)>=0 \ \& \ Signal(i+1)<0 \tag{3.14}$$

3.3.1.1.3 Hjorth Parameters: Hjorth parameters indicate three time domain features namely *Activity*, *Mobility* and *Complexity* to determine the strength of EEG signal (Hjorth, 1970; Kanno and Clarenbach, 1985).

(i) **Activity** is the measure of average power of the signal and was obtained by taking variance of the signal. For signal $x(t)$, the activity is (Hjorth, 1970):

$$Activity = var[x(t)] \tag{3.15}$$

(ii) **Mobility** is the standard deviation of the first time derivative of the EEG signal divided by standard deviation of the main signal. Mobility for signal $x(t)$ is (Hjorth, 1970) is calculated as:

$$Mobility = \frac{\sqrt{var(x(t)\cdot\frac{dx}{dt})}}{\sqrt{var(x(t))}} \tag{3.16}$$

(iii) **Complexity** indicates signal similarity in comparison to sine wave; where, higher similarity index is close to one and lower near to zero (Depoortere et al., 1993). It is defined as the Standard Deviation of double derivative of the signal to the first derivative and represents the spread of the spectrum (Hjorth, 1970).

$$Complexity = \frac{Mobility\ (\frac{dx(t)}{dt})}{Mobility\ (x(t))} \tag{3.17}$$

The Hjorth parameter measures the signal complexity and used for analysis of spectrum. These are the most efficient tool for representing event related desynchronization and synchronization activity (Oh et al., 2014).

3.3.1.1.4 Approximate Entropy (ApEn): Approximate Entropy quantifies the regularity in time series and predicts the future values based on previous values (Pincus, 1991); thus, it finds the system randomness and predictability. This feature may work even on small data points (i.e. even less than 50) and less affected by noise (Pincus, 1991). Clinically, entropy was in use for the study and detection of schizophrenia (Sabeti, 2009), epilepsy (Yuan, 2011). The Approximate Entropy of the signal can be calculated as (Pincus, 1991; Vukkadala et al., 2009; Reddy and Kulkarni, 2013):

For, signal length X_i ; X(i) = [x (i), x (i+1), …..x (i+m-1)] for $1 \leq i \leq N-m+1$ (3.18)

To find the new sequence with 'R' as criterion for similarity

Let R = k × Standard Deviation (k = 0.2 ~ 0.3); for each $1 \leq X(i), X(j) \leq N-m+1$, $i \neq j$

$$C_i^m(r) = \frac{\sum_{j=1}^{N-m+1} Dif\ [X(i),X(j)]}{N-m+1} \tag{3.19}$$

Where, $C_i^m(r)$ is the fraction of pattern length 'm' with similar resemblance to that of 'i'

Whereas, $Dif\ [X(i),X(j)]$ = {1, if $Dif\ [X(i),X(j)] \leq$ r ; 0, otherwise}

$$\Phi^m(r) = \frac{1}{N-m+1} \sum_{i=1}^{N-m+1} ln\, c_i^{m+1}(r); \tag{3.20}$$

ApEn can be calculated for new pattern series $\Phi^m(r)$ as:

$$ApEn = \Phi^m(r) - \Phi^{m+1}(r) \tag{3.21}$$

3.3.1.1.5 Lempel Ziv Complexity (LZ Complexity): LZ complexity measures the complexity of the signal in one-dimension with short epoch lengths (Lempel and Ziv, 1976; Aboy et al., 2006). It is similar to approximate entropy, but 40 times faster than ApEn calculation, because, ApEn lacks relative consistency (Richman and Moorman, 2000). LZ complexity has applications in finding randomness of finite sequences in information theory (Lempel et al., 1982), coding (Lapidoth and Ziv, 1998), data compression (Ziv and Lempel,

1978) and biosignals (Amigó et al., 2004; Wu and Xu, 1991). It is a strong tool to differentiate between rhythmic and non-rhythmic activity of EEG for detection of epileptic seizure.

To calculate LZ metrics, the discrete time biosignal is converted into the binary sequence. It categorizes the signal into 0 and 1 against reference value after matching with threshold (Td) (Aboy et al., 2006)

Where, $$s(i)=\begin{cases} 0, & if\ x(i) < Td \\ 1, & otherwise \end{cases} \quad (3.22)$$

In measure the complexity, the sequence is scanned from left to right, whereas, the complexity counter increased by 1 every time whenever a new count is encountered. The complexity is represented as c(n) (Aboy et al., 2006):

$$c(n) < \frac{n}{(1-\varepsilon n) log\alpha(n)} \quad (3.23)$$

Where, 'n' represents the length of sequence, εn is a small quantity and tends to be 0,

3.3.1.2 Frequency Domain Features

Since, there is a change in the frequency component of the EEG signals with change in mental activity; it is important to analyze the signal in frequency domain. The important features of frequency domain are:

3.3.1.2.1 Total Energy/Power: Total power in an EEG signal is the sum of the squared values in an epoch (Kumar and Anand, 2006). In frequency domain analysis, this is the sum of squared values of Fast Fourier Transform (FFT) magnitudes (Kumar and Anand, 2006). Let, signal be x(t); $x(t)=x_1, x_2, x_3, \ldots\ldots x_n$

$$\text{Total power} = \sum_{i=0}^{N-1} (x(t))^2 \quad (3.24)$$

3.3.1.2.2 Band Powers: It is defined as the Power in a particular frequency band (i.e. δ, θ, α, β, γ) divided by total power (Faulconer, 1952; Dressler et al., 2004). These are of four types:

(i) Delta Power: Delta power is the ratio of power in delta (δ) band (0.5 – 4 Hz) i.e. E_δ to the total power (E_T).

$$Delta\ Power = \frac{Power\ in\ Delta\ Band(E_\delta)}{Total\ Power(E_T)} \quad (3.25)$$

(ii) Theta power is the ratio of power in theta band (E_θ) to the total power (E_T) (Liu et al., 2008).

$$Theta\ Power = \frac{Power\ in\ Theta\ Band(E_\theta)}{Total\ Power(E_T)} \tag{3.26}$$

(iii) Alpha power is the ratio of power in alpha (α) band (E_α) to the total power (E_T) (Liu et al., 2008).

$$Alpha\ Power = \frac{Power\ in\ Alpha\ Band(E_\alpha)}{Total\ Power(E_T)} \tag{3.27}$$

(iv) Beta power is the ratio of power in beta (β) band (E_β) to the total power (E_T) (Liu et al., 2008).

$$Beta\ Power = \frac{Power\ in\ Beta\ Band(E_\beta)}{Total\ Power(E_T)} \tag{3.28}$$

These band powers had shown significant inferences when compared with intelligent quotient of students. It was found that Delta power was more in brighter student in comparison to mediocre students (Liu et al., 2008).

3.3.1.2.3 Delta (δ) Ratio: Delta ratio is a ratio of two band powers i.e. total power in alpha and beta band to delta band (Rizon, 2010). Delta ratio stabilizes the band related changes in the EEG quotient.

$$\delta\ Ratio = \frac{E_\alpha + E_\beta}{E_\delta} \tag{3.29}$$

Where, E_α is power in alpha band, E_β is power in beta band and E_δ is power in delta band.

3.3.1.2.4 BA Ratio: BA ratio is the ratio of power in beta band (E_β) to alpha band (E_α) (Traast and Kalkman, 1995).

$$BA\ Ratio = \frac{E_\beta}{E_\alpha} \tag{3.30}$$

The BA ratio was useful with visual search ability and thus an effective tool to measure any change in VEP responses (Liu et al., 2008).

3.3.1.2.5 Beta (β) Ratio: β-Ratio is the log ratio of two empirically derived bands i.e. β-band power to total power in an epoch (Seifert et al., 1993).

$$Beta\ Ratio = log_{10} \frac{(P_{13-30\ Hz})}{(P_{Total})} \quad (3.31)$$

Where, $P_{13\text{-}30\ Hz}$ = Power contained in frequency band 13-30 Hz and,

$P_{total\ Hz}$ = Power contained in total frequency band

3.3.1.2.6 Median Power Frequency (MPF): Median Power Frequency is defined as the frequency, which divides the total power contained in the signal in two halves. In other words, it is that frequency below which 50% of the total power of the signal resides (Sharpe, 1997). It has a fluctuating nature, where, it decreases with sedation and increases with deep sleep (Sharpe, 1997). The MPF for signal x(n) is calculated as

Calculate the width for a time series:

$$W(x_n) = x_n(i+1)-x_n(i); \quad (3.32)$$

Calculating the difference between two points height (for effective triangle area)

$$Wd(i) = \frac{x(i+1)+x(i)}{2 \times W(x)}; \quad (3.33)$$

where, Wd is the difference between two peak points,

Total Area (Wtotal) or MPF = $\frac{Wd(i)}{2}$、 (3.34)

3.3.1.2.7 Spectral Edge Frequency (SEF): It is a frequency below which 95% of the total EEG power is localised (Rampil and Matteo, 1989). It has a strong significance during relaxed and awake state with intra-individual specificity (Rampil and Matteo, 1989; Schwender, 1996). It does vary with sedation like anaesthetics and a good tool to measure the change in frequency band. The SEF varies when signal power shifts from one frequency range to another. The SEF for signal x(n) can be calculated as:

Calculate the width of the signal;

$$W(x_n) = x_n(i+1)-x_n(i); \quad (3.35)$$

Effective triangle area between two points height

$$Wd= x(i+1)-x(i); \quad (3.36)$$

where, Wd is the difference between two peak points,

and area of square: Ws = x(i) × W(x_n);

Calculate the area of triangle; Wt = 0.5 × W(x_n) × Wd;

Total Area; Wtotal = Ws + Wt;

$$\text{Spectral content or SEF} = 95\% \times \text{Wtotal} \tag{3.37}$$

3.3.1.2.8 Spectral Entropy (SpEn): Approximate Entropy measures the randomness in the time-domain EEG signal, whereas, uncertainty in the frequency domain is measured by spectral entropy (Rezek and Roberts, 1998; Richman and Moorman, 2000). Spectral entropy is calculated by multiplying the power in each frequency by the logarithm of the same power i.e.

$$SpEn = \sum_f P_f \log\left(\frac{1}{P_f}\right) \tag{3.38}$$

Where, P_f is the power in each frequency.

The spectral entropy has sensitive deflection for motor imagery tasks and is mostly used in Brain Computer Interface (BCI) for measuring movement abilities (Zhang et al., 2008).

3.3.1.3 Time and Frequency Feature Analysis

Time and Frequency features were extracted in 62 subjects (relaxed subjects-32 + alcoholic/controlled subjects-30). All the computations were made in MATLAB R2009b (Propriety of Mathworks). The detailed description of features (database wise) and their analysis is described below.

3.3.1.3.1 Analysis on Relaxed State Subjects (Dataset 1)

The time and frequency features were extracted for dataset 1 i.e. the EEG signals taken in the relaxed state from the central and parietal region of brain, for the subjects in relaxed state with eyes open from parietal region of brain. Table 3.2 shows the extracted features from the **subject 1** with 30 trails (all three sessions). Similarly, features extracted from all other subjects i.e. rest of 31. Due to space constrain, extracted features from the only one subject (subject 1) is shown here (Table 3.2).

Table 3.2 Time and Frequency features of Subject-1 during Relaxed State

Trials	Vrms	Activity	Mobility	Complx.	Avg. Freq.	Approx. Entropy	LZ Complx	T. Power	Delta Power	Theta Power	Alpha Power	Beta Power	Delta Ratio	B Ratio	BA Ratio	MPF	SEF	Sp En
Tr_1	0.120	0.015	0.124	1.796	97.00	0.37	95.00	28.19	35.25	18.58	0.96	26.85	0.79	0.16	27.97	18.00	41.50	21.76
Tr_2	0.121	0.020	0.120	1.919	93.00	0.40	98.00	38.36	35.68	26.24	0.92	18.09	0.53	0.31	19.63	18.75	41.50	7.49
Tr_3	0.119	0.012	0.133	1.669	88.00	0.46	89.00	22.75	41.41	6.29	0.51	31.67	0.78	0.27	62.13	15.00	42.25	16.69
Tr_4	0.110	0.012	0.150	1.549	90.00	0.40	89.00	23.35	33.96	7.32	1.18	27.82	0.85	0.34	23.59	17.25	42.25	26.81
Tr_5	0.122	0.015	0.127	1.843	82.00	0.42	80.00	25.66	29.23	25.66	0.73	20.48	0.73	0.34	27.93	18.23	42.50	20.87
Tr_6	0.122	0.033	0.084	2.650	64.00	0.35	93.00	55.84	69.90	5.84	0.66	14.14	0.21	0.21	21.42	19.11	39.00	0.11
Tr_7	0.128	0.025	0.099	2.258	72.00	0.48	94.00	43.57	54.58	12.36	1.04	18.86	0.36	0.10	18.16	12.75	40.00	4.05
Tr_8	0.120	0.017	0.125	1.818	92.00	0.44	92.00	29.52	33.59	17.07	0.83	26.80	0.82	0.20	32.45	16.00	41.75	17.24
Tr_9	0.117	0.012	0.140	1.642	99.00	0.42	94.00	23.05	30.35	16.80	0.92	26.99	0.92	0.26	29.41	17.75	42.75	29.26
Tr_10	0.122	0.022	0.110	2.078	76.00	0.40	80.00	42.28	45.18	20.39	0.53	18.49	0.42	0.14	34.89	13.50	41.50	5.06
Tr_11	0.127	0.025	0.100	2.215	84.00	0.38	87.00	45.02	59.48	6.90	0.40	20.72	0.36	-0.01	51.22	15.08	40.25	8.34
Tr_12	0.113	0.013	0.130	1.627	81.00	0.40	80.00	23.29	29.37	5.54	1.45	45.34	1.59	-0.06	31.22	17.75	41.00	23.55
Tr_13	0.110	0.005	0.142	1.503	85.00	0.48	85.00	22.90	20.12	6.96	1.20	50.74	2.58	-0.07	42.41	19.25	41.75	33.99
Tr_14	0.112	0.529	0.152	1.482	101.00	0.41	97.00	24.42	21.33	6.31	1.37	43.43	2.10	0.00	31.61	18.25	42.25	32.36
Tr_15	0.123	0.012	0.152	1.489	98.00	0.40	91.00	22.67	25.35	8.11	2.31	33.64	1.42	0.17	14.53	19.00	42.50	31.08
Tr_16	0.111	0.230	0.155	1.457	104.00	0.40	99.00	24.65	23.09	6.39	1.98	40.06	1.82	0.08	20.25	18.75	41.75	33.47
Tr_17	0.121	0.015	0.147	1.542	91.00	0.46	90.00	26.89	28.58	7.79	2.27	33.51	1.25	0.29	14.74	19.25	41.75	22.89
Tr_18	0.120	0.010	0.150	1.460	90.00	0.55	90.00	17.71	13.87	6.14	1.55	50.07	3.72	0.09	32.27	20.50	42.75	60.07
Tr_19	0.113	0.256	0.168	1.361	109.00	0.52	97.00	18.67	18.00	4.56	1.44	41.12	2.37	0.38	28.48	21.75	43.25	49.17
Tr_20	0.109	0.021	0.162	1.431	106.00	0.52	97.00	23.26	23.54	9.33	0.94	31.37	1.37	0.40	33.41	20.00	42.00	32.98
Tr_21	0.123	0.015	0.126	1.832	98.94	0.47	96.90	28.76	35.95	18.95	0.98	27.38	0.80	0.16	28.53	15.10	42.33	22.20
Tr_22	0.122	0.020	0.122	1.958	94.86	0.42	99.96	39.12	36.39	26.76	0.94	18.45	0.54	0.31	20.02	18.90	42.33	7.64
Tr_23	0.120	0.520	0.136	1.702	89.76	0.47	90.78	23.20	42.23	6.41	0.52	32.31	0.79	0.27	63.38	15.30	43.10	17.03
Tr_24	0.112	0.123	0.153	1.580	91.80	0.41	90.78	23.82	34.64	7.46	1.20	28.38	0.87	0.35	24.06	17.60	43.10	27.35
Tr_25	0.124	0.015	0.130	1.879	83.64	0.42	91.60	26.17	29.81	26.17	0.75	20.89	0.74	0.35	28.49	19.02	43.35	21.29
Tr_26	0.123	0.034	0.086	2.703	65.28	0.45	64.26	56.95	71.30	5.96	0.67	14.42	0.22	0.21	21.84	15.30	39.78	0.11
Tr_27	0.128	0.025	0.101	2.303	73.44	0.49	95.48	44.44	55.67	12.61	1.06	19.24	0.37	0.10	18.52	18.03	40.80	4.13
Tr_28	0.120	0.017	0.128	1.855	93.84	0.41	93.84	30.11	34.26	17.41	0.84	27.33	0.84	0.21	33.09	16.12	42.59	17.58
Tr_29	0.111	0.012	0.142	1.674	100.98	0.43	95.88	23.51	30.96	17.14	0.94	27.53	0.94	0.27	30.00	16.07	43.61	29.85
Tr_30	0.122	0.022	0.112	2.119	77.52	0.42	91.98	43.12	46.08	20.80	0.54	18.86	0.43	0.14	35.59	17.89	42.33	5.16

In order to find the variation between the different trials of the same person (intra-individual) and between the different persons (inter-individual), Analysis of Variance (ANOVA) was employed. ANOVA is a statistical tool to find significant differences between two or more means (Ostertagová and Ostertag, 2013; Armstrong et al., 2000; McCluskey and Lalkhen, 2007). The one way ANOVA was performed on Microsoft Office Excel 2007®. Intra and inter variation observed for different parameters with 'P' value that tests the null hypothesis taking Alpha (α=0.05) as level of significance (Table 3.3 for dataset 1).

Table 3.3 ANOVA analysis on Relaxed State Subjects

Parameters	Inter Subject (Between subjects), P value (α=0.05)	Intra Subject (Between trials), P value (α=0.05)
RMS	***1.63346E-342***	***0.99999998***
Activity	1.44499E-178	0.79727400
Mobility	4.20872E-268	0.29799325
Complexity	2.44660E-98	0.53151831

Avg. Frequency	0.00000E+00	0.79999837
Entropy	***2.68157E-264***	***0.99996918***
LZ Complexity	***0.00000E+00***	***0.99999999***
T. Power	7.75176E-171	0.39773291
Delta Power	2.95782E-193	0.04291538
Theta Power	1.59535E-103	0.32464604
Alpha Power	1.11217E-232	0.78543278
Beta Power	2.19428E-182	0.74023968
Delta Ratio	1.04152E-108	0.86011733
B Ratio	2.32364E-19	0.59999991
BA Ratio	2.38254E-125	0.57173370
MPF	***2.34224E-119***	***0.99999991***
SEF	***2.23258E-23***	***0.99999993***
Sp En	2.58236E-193	0.40915380

From the Table 3.3, it can be seen that 'P' value for inter subject analysis is very close to zero, which shows statistical significant differences between the subjects. Whereas, in case of intra-subject analysis (i.e. subject trials) almost each value is higher than Alpha (0.05) except for Delta power, indicating that there is no statistical difference between trials/observation. Moreover, it was observed that the maximum intra-subject variation (higher 'P' value) was observed in case of RMS, Entropy, LZ Complexity, MPF and SEF features. These features are used for verification purpose. It was concluded from the above study that significant results can be inferred for biometric when 'P' value lie "close to one" for intra-subject variation and "zero" for inter-subject variation.

3.3.1.3.2 Analysis on Alcoholic/Controlled Disposition Subjects (Dataset 2)

The time and frequency features were extracted for data set 2 i.e. EEG signal dataset of alcoholic/controlled disposition subjects from prefrontal cortex (single channel, Fp1); because the maximum activation is found in lateral frontal cortex when examined by imaging research (Duncan et al., 2000; Cacioppo et al., 2000; Begleiter and Porjesz, 1999).

Table 3.4 shows the extracted features from subject 1 with 30 trails (all three sessions). The extracted features from all other subjects i.e. rest of 29 are not shown due to space constrain.

Table 3.4 Time and Frequency features of Subject-1 during Alcoholic/Controlled Disposition State

Trials	Vrms	Activity	Mobility	Complx.	Avg. Freq.	Approx. Entropy	LZ Complx	T. Power	Delta Power	Theta Power	Alpha Power	Beta Power	Delta Ratio	B Ratio	BA Ratio	MPF	SEF	Sp En
Tr_1	3.99	16.00	0.18	1.52	8.00	0.51	8.00	79.00	37.52	0.41	3.56	18.76	1.19	30.49	1.10	10.00	35.00	3.13
Tr_2	3.33	11.13	0.16	1.47	5.00	0.24	7.00	49.65	26.10	0.38	3.44	11.73	1.06	25.80	-0.48	12.00	30.00	5.10
Tr_3	4.50	20.34	0.13	1.68	4.00	0.25	8.00	11.22	47.69	0.31	3.94	9.38	0.96	18.76	0.68	10.00	30.00	2.48
Tr_4	4.43	80.30	0.07	1.34	2.00	0.28	6.00	42.00	18.84	0.17	3.15	4.69	0.14	14.07	0.27	15.00	40.00	0.15
Tr_5	6.98	72.40	0.06	2.17	1.00	0.36	8.00	46.27	17.02	0.15	5.09	2.35	0.13	11.73	-0.34	16.00	30.00	0.11
Tr_6	12.34	33.20	0.07	2.32	2.00	0.21	7.00	18.23	79.20	0.17	5.44	4.69	0.18	14.07	-0.56	15.00	30.00	0.21
Tr_7	4.38	19.30	0.11	1.93	4.00	0.27	7.00	10.80	45.26	0.25	4.54	9.38	0.63	16.42	-0.37	10.00	35.00	2.96
Tr_8	4.21	57.29	0.11	2.19	3.00	0.25	6.00	31.62	34.21	0.26	5.13	7.04	0.58	14.07	0.14	12.00	30.00	0.99
Tr_9	3.98	12.76	0.09	2.23	3.00	0.20	6.00	68.17	64.21	0.22	5.23	7.04	0.47	14.07	-0.43	16.00	30.00	0.54
Tr_10	5.38	29.06	0.11	1.98	4.00	0.25	8.00	17.29	68.16	0.26	4.65	9.38	0.58	18.76	-0.44	10.00	30.00	1.93
Tr_11	4.12	17.06	0.20	1.34	5.00	0.24	9.00	5.84	40.00	0.47	3.15	11.73	1.40	23.45	0.63	20.00	35.00	3.67
Tr_12	3.96	15.78	0.14	1.72	3.00	0.31	8.00	7.46	37.00	0.32	4.03	7.04	0.84	18.76	-0.22	10.00	35.00	3.84
Tr_13	5.83	34.07	0.10	2.06	4.00	0.24	9.00	20.47	79.89	0.24	4.82	9.38	0.57	21.11	0.72	15.00	30.00	1.34
Tr_14	3.45	11.23	0.07	1.37	2.00	0.25	6.00	59.20	26.40	0.17	3.22	4.69	0.12	14.07	0.30	15.00	40.00	0.11
Tr_15	3.40	11.90	0.06	2.20	0.00	0.25	7.00	17.17	26.20	0.14	5.16	0.00	0.10	7.04	-0.38	10.00	30.00	0.08
Tr_16	2.09	48.90	0.07	2.26	2.00	0.27	8.00	15.31	11.48	0.17	5.29	4.69	0.16	11.73	-0.54	15.00	25.00	0.15
Tr_17	4.55	20.81	0.09	2.14	2.00	0.21	9.00	12.51	48.79	0.21	5.01	4.69	0.50	9.38	-0.49	10.00	30.00	2.46
Tr_18	4.30	53.56	0.12	2.00	4.00	0.27	8.00	29.42	125.60	0.27	4.69	9.38	0.63	18.76	-0.16	13.00	25.00	1.14
Tr_19	5.03	13.66	0.09	2.19	4.00	0.21	7.00	79.25	35.23	0.22	5.13	9.38	0.49	16.42	-0.46	15.00	30.00	0.49
Tr_20	4.21	38.08	0.09	2.40	3.00	0.25	6.00	22.91	89.31	0.21	5.64	7.04	0.58	14.07	-0.72	14.00	25.00	1.41
Tr_21	4.07	16.32	0.18	1.55	8.16	0.52	10.00	17.17	38.27	0.42	3.63	19.14	1.21	31.10	1.12	15.10	35.70	3.20
Tr_22	3.40	11.35	0.17	1.49	5.10	0.27	9.00	14.75	26.62	0.39	3.51	11.96	1.08	26.31	-0.49	10.20	30.60	5.20
Tr_23	4.59	20.74	0.14	1.71	4.08	0.42	8.16	11.44	48.64	0.32	4.02	9.57	0.98	19.14	0.69	12.40	30.60	2.53
Tr_24	4.98	18.97	0.07	1.37	2.04	0.16	8.21	43.20	19.22	0.17	3.21	4.78	0.15	14.35	0.27	15.30	30.00	0.15
Tr_25	4.34	16.92	0.06	2.21	1.02	0.27	5.10	47.30	14.72	0.15	5.19	2.39	0.14	11.96	-0.35	10.20	30.60	0.12
Tr_26	6.13	34.20	0.07	2.36	2.04	0.18	7.98	20.01	80.06	0.17	5.55	4.78	0.18	14.35	-0.57	15.10	25.50	0.21
Tr_27	4.47	19.69	0.11	1.97	4.08	0.27	9.10	11.02	46.17	0.26	4.63	9.57	0.64	16.74	-0.37	10.20	30.00	3.02
Tr_28	7.71	58.43	0.11	2.23	3.06	0.25	7.00	32.25	13.70	0.26	5.24	7.18	0.59	14.35	0.14	16.90	25.50	1.01
Tr_29	4.80	14.85	0.09	2.27	3.06	0.20	7.00	69.53	69.20	0.22	5.33	7.18	0.48	14.35	-0.44	15.10	25.50	0.55
Tr_30	5.49	29.64	0.11	2.02	4.08	0.25	8.16	17.64	69.52	0.26	4.75	9.57	0.59	19.14	-0.45	10.20	30.60	1.97

In this case also, ANOVA analysis was employed on all feature sets of subjects. Table 3.5 depicts one way ANOVA analysis on subjects for intra and inter individual differences with 'P' value, taking Alpha (α=0.05) as level of significance for all the features for alcoholic/controlled disposition subjects.

Table 3.5 ANOVA analysis on Alcoholic/Controlled Disposition Subjects

Parameters	Inter Subject (Between subjects), P value (α=0.05)	Intra Subject (Between trials), P value (α=0.05)
Vrms	***8.95242E-20***	***0.9757167***
Activity	1.75496E-14	0.3086641
Mobility	2.08882E-44	0.0183596
Complexity	1.21252E-26	0.0039250
Avg. Frequency	3.00209E-31	0.0118285

Entropy	***6.9194E-37***	***0.5246290***
LZ Complexity	***4.32364E-19***	***0.7781946***
T. Power	3.40735E-13	0.3283348
Delta Power	2.10291E-44	0.0385554
Theta Power	1.22771E-16	0.0044576
Alpha Power	3.72462E-14	0.0852536
Beta Power	2.45420E-44	0.2013457
Delta Ratio	4.52676E-26	0.3924234
B Ratio	3.23333E-23	0.0334235
BA Ratio	3.48466E-45	0.3965238
MPF	***1.61169E-22***	***0.8041066***
SEF	***7.07883E-31***	***0.8823266***
Sp En	4.48266E-56	0.4962771

From the Table 3.5, it is evident that 'P' value for inter subject analysis is very close to zero, which shows statistical significant differences between the subjects. Whereas, in case of intra-subject analysis (i.e. subject trials) almost half of the values for feature sets lies below the alpha value, which infers the statistical significant difference exist between trials which means there is no similarity between the trial observations. Except for some selected features (RMS, Entropy, LZ Complexity, MPF and SEF) whose 'P' values lie above the Alpha and near to one, where some difference exists; thus, these features will be used for verification purpose.

From both type of dataset it is observed that there was adequate variation in some features for the intra and inter subject differences; hence, these features fulfill the need of biometric matching requirements.

3.3.2 Non Linear Features of EEG

The non linear analysis was employed on subjects undergoing mental activity tasks (dataset 3) because of high variation in EEG potential whenever task switched from baseline to higher mental cognition like multiplication, figure rotation etc. Two non linear features i.e. Higuchi Fractal dimension (HFD) and Correlation Dimension (CD/CorrD) were used for feature extraction and analysis from EEG biosignals. These features indicate the chaotic behaviour of signal and measure the linearity amongst non linear things (Theiler, 1990). Application of HFD on Brain Computer Interface had already been investigated during imagery tasks ((Weiss et al., 2011; Loo et al., 2011). One of the important analysis by Correlation Dimension includes the study of different mental states (Natarajan et al., 2004).

3.3.2.1 Higuchi Fractal Dimension

The Fractal Dimension measures the statistical index of complexity by measuring the fractal pattern that changes over time scale (Falconer, 2003). Higuchi Fractal Dimension (HFD) is a non-linear measurement technique which is used to study EEG stochastic behaviour (Higuchi, 1998). Fractal dimension has several advantages like robustness against artefacts, simple and fast computing. However, it is sensitive to numerical or experimental noise and the amount of data. The mathematical expression for Fractal Dimension is given as under:

For a given time series $x = \{x(1), x(2)\ldots, x(N)\}$,

A new time series constructed for m=1, 2….. and k_{max}=5, where, m and k are integers (Falconer, 2003).

$$x_m^k = \left[x(m), x(m+k), \ldots, x\left(m + \left[\frac{N-m}{k}\right]\right).k\right] \tag{3.39}$$

Where, m and k denotes the initial time and time interval respectively. The length, $L_m(k)$ of each curve is computed as:

$$L_m(k) = \frac{1}{k}\left(\sum_{i=1}^{\left[\frac{N-m}{k}\right]} x(m+ik) - x(m+(i-1)k)\right)\frac{N-1}{\left[\frac{N-m}{k}\right]k} \tag{3.40}$$

The Fractal Dimension "D" then is computed as (Higuchi, 1998),

$$D = \left[\frac{\log_2(L_m(k))}{\log_2 k}\right] \tag{3.41}$$

3.3.2.2 Correlation Dimension (CorrD or CD)

Correlation Dimension (CorrD or CD) is a good estimator of complex signal behaviour and useful for finding the underlying information within the signal by extracting the irregularity degree from the signal trajectory in the space (Grassberger and Procaccia, 1983a). It measures the data even in small vicinity corresponding to neighbouring points in a trajectory and a basic measure of attractors. The word "attractor" used here is basically a point where whole dynamics of system tries to assimilate for stability (Grassberger and Procaccia, 1983b). It can work on small data points; however, it needs higher computation time to construct phase space plot.

Correlation dimension measures the average number of data points in a radius "r" of data X_y.

$$Correlation\ Dimension\ (CD) = \lim_{r=0} log\ (C_r)/log\ (r) \qquad (3.42)$$

Where, C_r is Correlation Integral is given as (Grassberger and Procaccia, 1983a),

$$C(r) = \frac{1}{(N-\theta\min)\ (\mathrm{N}-\theta min-1)} \sum_{x=1}^{N} \sum_{y=x+\theta min}^{N} \alpha(r - |X_x - X_y|) \qquad (3.43)$$

Where, $X_x$and X_y are the points of trajectory in space, N is the total number of data points, r is the radial distance, α is the Heaviside function, θmin is the average correlation time i.e. the time where autocorrelation decays to 1/e (Acharya, 2005).

3.3.2.3 Feature Analysis

Non-linear features (Fractals and Correlation dimension) were extracted from mental ability tasks (dataset 3) from all the four channels i.e. C3, C4, P3 and P4. The task wise feature analysis of the subjects is shown in Table 3.6 and 3.7. The values (shown in Table 3.6 and 3.7) are mean of 5 trials with standard deviation of less than ± 5%.

Table 3.6 HFD and CorrD features from Central Region of Brain

Task/Subjects		**Sub#1**		**Sub#2**		**Sub#3**		**Sub#4**		**Sub#5**	
Task	**Method**	C3	C4	C3	C4	C3	C4	C3	C4	C3	C4
Task-1 Baseline	HFD	1.749	1.646	1.437	1.484	1.618	1.864	1.673	1.725	1.679	1.569
	CorrD	0.973	0.983	0.973	0.973	0.978	0.952	0.973	0.972	0.971	0.980
Task-2 Counting	HFD	1.674	1.557	1.467	1.579	1.606	1.689	1.877	1.896	1.741	1.677
	CorrD	0.972	0.972	0.973	0.979	0.975	0.978	0.980	0.982	0.979	0.985
Task-3 Letter Co.	HFD	1.704	1.574	1.400	1.481	1.640	1.700	1.615	1.619	1.642	1.556
	CorrD	0.978	0.973	0.971	0.984	0.984	0.976	0.978	0.977	0.974	0.985
Task-4 Multipl.	HFD	1.746	1.653	1.546	1.560	1.595	1.622	1.815	1.823	1.811	1.661
	CorrD	0.970	0.970	0.976	0.975	0.980	0.974	0.971	0.940	0.978	0.978
Task-5 Rotation	HFD	1.723	1.601	1.580	1.654	1.566	1.713	1.814	1.860	1.852	1.792
	CorrD	0.971	0.970	0.969	0.968	0.972	0.977	0.975	0.977	0.980	0.977

Table 3.7 HFD and CorrD features from Parietal Region of Brain

Task/Subjects		**Sub#1**		**Sub#2**		**Sub#3**		**Sub#4**		**Sub#5**	
Task	**Method**	P3	P4	P3	P4	P3	P4	P3	P4	P3	P4
Task-1 Baseline	HFD	1.709	1.736	1.471	1.483	1.542	1.648	1.701	1.748	1.629	1.603
	CorrD	0.975	0.970	0.980	0.969	0.975	0.964	0.976	0.979	0.973	0.983
Task-2 Counting	HFD	1.738	1.694	1.456	1.489	1.533	1.527	1.869	1.893	1.693	1.639
	CorrD	0.975	0.978	0.979	0.977	0.974	0.969	0.980	0.984	0.972	0.978
Task-3	HFD	1.705	1.693	1.415	1.427	1.507	1.491	1.644	1.671	1.645	1.636

Letter Co.	CorrD	0.974	0.972	0.970	0.970	0.979	0.976	0.977	0.973	0.980	0.979
Task-4 Multipl.	HFD	1.745	1.775	1.520	1.523	1.551	1.527	1.808	1.805	1.734	1.630
	CorrD	0.974	0.972	0.975	0.977	0.974	0.975	0.986	0.982	0.971	0.973
Task-5 Rotation	HFD	1.774	1.722	1.573	1.581	1.440	1.470	1.787	1.831	1.778	1.724
	CorrD	0.974	0.967	0.974	0.972	0.977	0.975	0.977	0.966	0.983	0.973

The non-linear features of Subject 1 are shown in Fig. 3.18 from all channels and for all mental ability tasks.

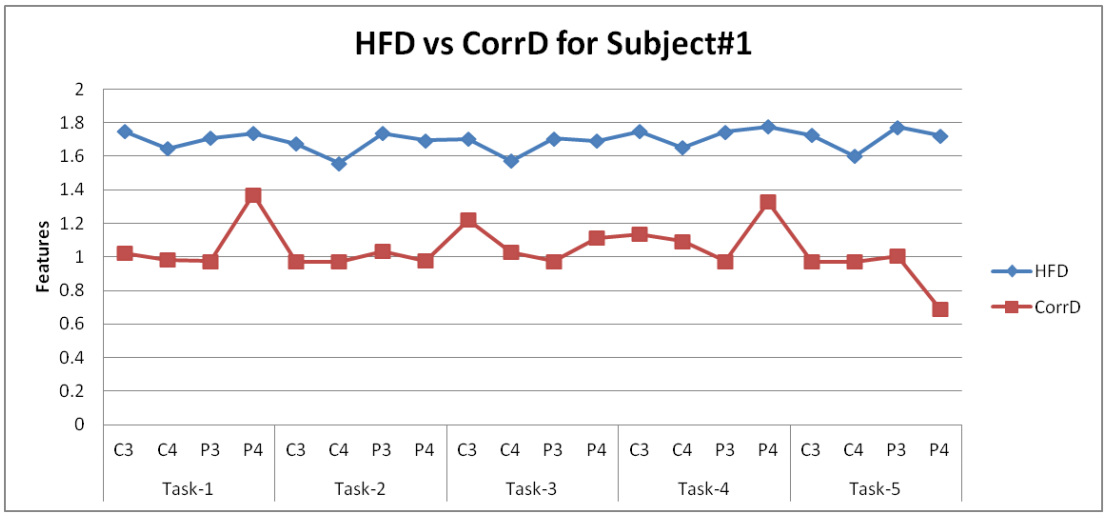

Fig. 3.18 HFD and CorrD for Subject-1 for all Mental Task Abilities

3.4 Summary

In this chapter, the EEG database of 1960 samples from 67 subjects (with three different mental state) have been processed and selected for EEG biometric verification. The acquired signals were pre-processed with Fast Independent Component Analysis (FastICA) to remove any ocular artefacts (EOG artefacts) from contaminated EEG signal. The retrieved pure signal demonstrated improved Signal to Noise Ratio.

After the pre-processing of EEG signals, features were acquired using Linear (Time and Frequency) and Non-linear (HFD and CD) techniques. From 18 features of Time and Frequency domain, the best 05 features (i.e. Entropy, LZ complexity, MPF, SEF and Vrms) were selected based on minimum intra and maximum inter variation, using statistical Analysis of Variance (ANOVA) technique. The non linear features (HFD and CD) were found suitable for mental ability tasks because of high variations were involved in switching mental thoughts from baseline to multiplication etc.

CHAPTER 4

EEG based Verification System

4.1 Verification System

Verification is a process in which an individual's biometric sample is compared with a previously enrolled data of that person (Jain et al., 2007). It is a matching process of one to one (1: 1). The system authenticates and verify the claim of a user who gives his/her identity by presenting the biometric sample. A verification system comprises of two steps (i) Enrollment and (ii) Authentication. A block diagram representing the EEG verification system is shown in Figure 4.1.

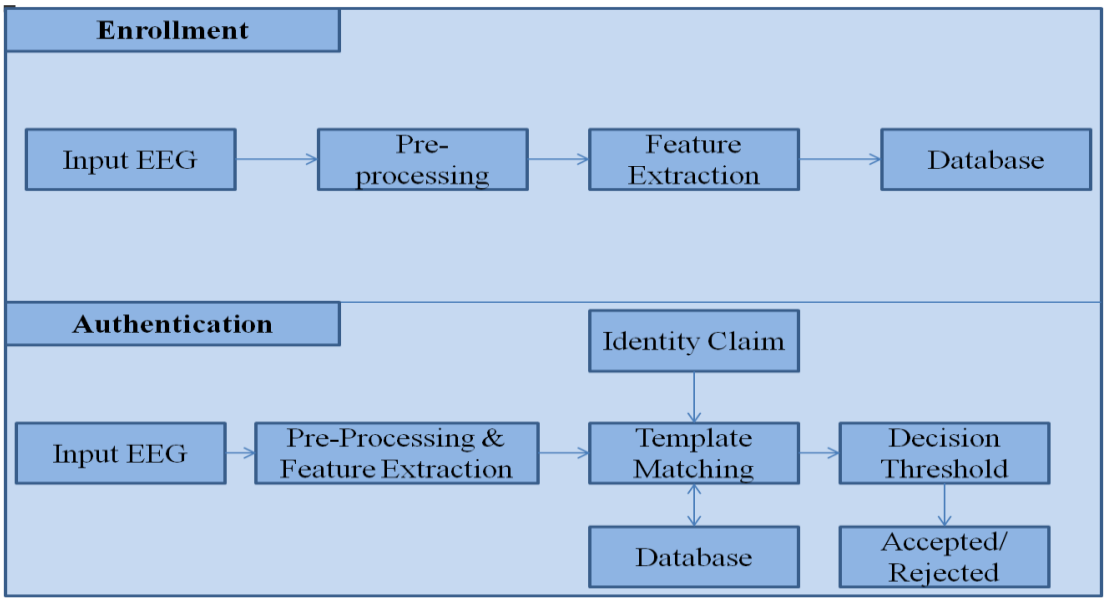

Fig. 4.1 Verification System for EEG (Enrollment and Authentication)

In enrollment phase, new users are enrolled into the system. New users are designated with name, password followed by users biometric information i.e. EEG sample. First of all, the provided information (i.e. name) is verified by the system; in case the same name exist then unique ID and password is asked by the user. Once this stage is passed, his/her biometric sample is asked to be presented for further evaluation and authentication.

4.2 Authentication Module on Raw Data with Varying Threshold

In this work, three types of EEG dataset were used i.e. (i) Relaxed state dataset; (ii) Visual stimuli dataset of controlled/alcoholic disposition subjects and (iii) Cognitive/ mental ability task dataset. The authentication was performed separately for these available dataset. In case of third type of dataset (i.e. Cognitive tasks), non-linear feature extraction technique was employed with Advance Machine learning approach for subject classification. Initially, the subject verification was achieved by performing three levels of security threshold. The selection of security threshold is discussed below:

4.2.1 Threshold Selection

The performance of the system was measured with three levels of security threshold as follows:

(a) High level security with 5% as threshold.
(b) Medium level security with 10% as threshold.
(c) Low level security with 15% as threshold.

The flow chart describing the authentication module is shown in Figure 4.2. In this system, extracted features (explained in previous chapter) from a particular subject are stored in the database template and used for matching one to one verification whenever a query sample is presented after enrollment.

4.2.2 Results of Verification in Relaxed State (Dataset 1)

The relaxed state condition constituted 32 subjects. The individual FAR and FRR were calculated for selected best features (Approximate Entropy, LZ Complexity, MPF, SEF and RMS) from a group of 18 features of time and frequency domain, based on minimum intra and maximum inter individual differences.

A comparative analysis of FRR (Table 4.1) and FAR (Table 4.2) done at three security thresholds i.e. at 5%, 10% and 15% is given below:

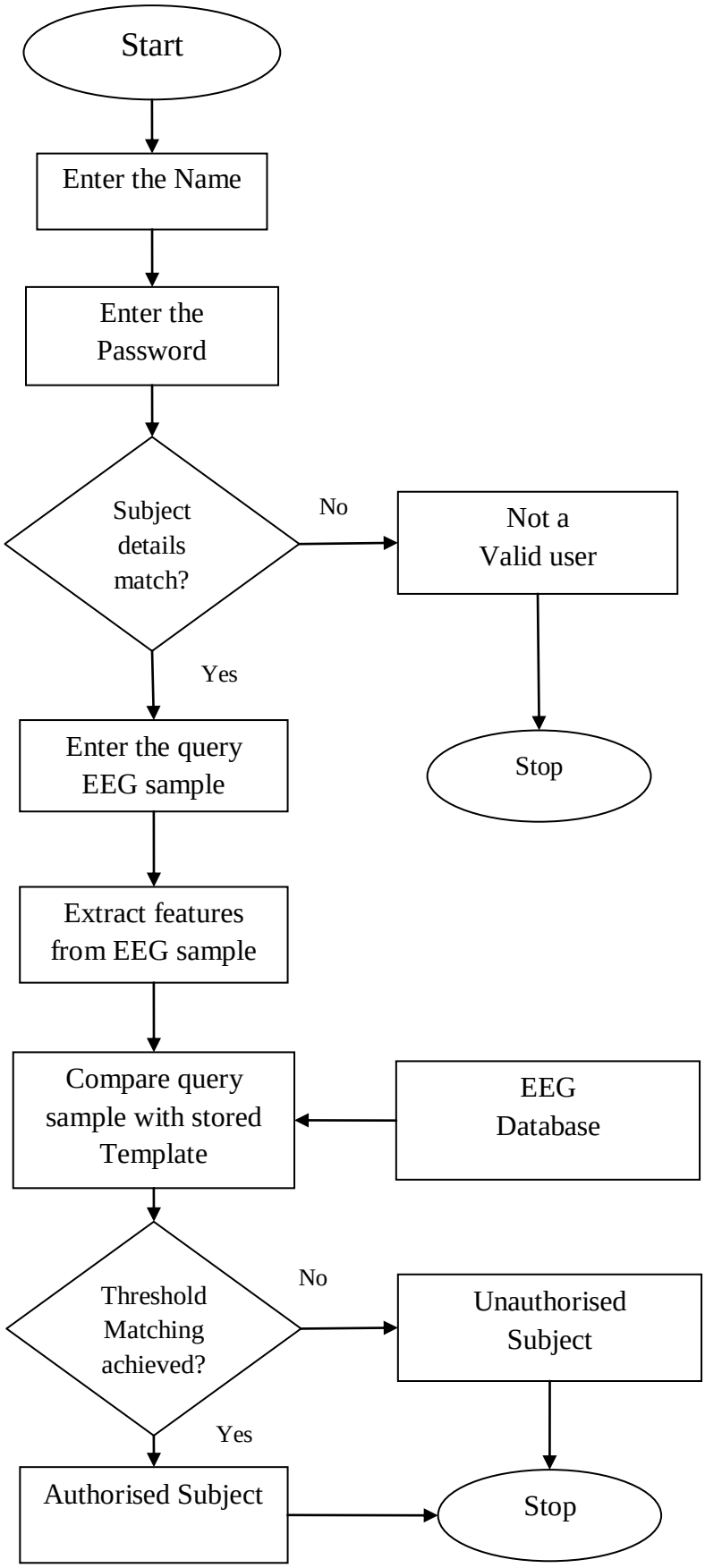

Figure 4.2 Flow Chart of Authentication System

Table 4.1 FRR of Subjects in Relaxed State with Varying Threshold

Sub	Entropy			LZ Complx			MPF			SEF			RMS		
	Threshold			Threshold			Threshold			Threshold			Threshold		
	5%	10%	15%	5%	10%	15%	5%	10%	15%	5%	10%	15%	5%	10%	15%
Sub_1	16.67	13.33	3.33	20.00	13.33	6.67	20.00	13.33	10.00	30.00	23.33	0.00	13.33	10.00	3.33
Sub_2	13.33	10.00	3.33	20.00	16.67	13.33	16.67	13.33	0.00	26.67	20.00	13.33	20.00	10.00	0.00
Sub_3	20.00	10.00	0.00	16.67	16.67	10.00	13.33	10.00	6.67	20.00	16.67	10.00	13.33	10.00	6.67
Sub_4	23.33	13.33	10.00	20.00	13.33	10.00	16.67	13.33	10.00	16.67	13.33	6.67	30.00	23.33	10.00
Sub_5	16.67	13.33	3.33	20.00	10.00	13.33	26.67	20.00	10.00	26.67	16.67	6.67	20.00	13.33	3.33
Sub_6	23.33	20.00	10.00	20.00	16.67	10.00	16.67	10.00	10.00	13.33	10.00	3.33	23.33	10.00	6.67
Sub_7	13.33	6.67	0.00	16.67	10.00	6.67	20.00	13.33	13.33	23.33	13.33	10.00	33.33	20.00	10.00
Sub_8	23.33	16.67	0.00	20.00	16.67	6.67	20.00	10.00	0.00	23.33	10.00	10.00	13.33	10.00	0.00
Sub_9	23.33	20.00	13.33	10.00	10.00	6.67	20.00	10.00	10.00	13.33	6.67	6.67	16.67	6.67	3.33
Sub_10	26.67	23.33	10.00	16.67	10.00	3.33	16.67	10.00	10.00	20.00	13.33	6.67	26.67	16.67	10.00
Sub_11	20.00	16.67	10.00	10.00	6.67	3.33	23.33	20.00	13.33	13.33	10.00	10.00	16.67	13.33	3.33
Sub_12	26.67	20.00	10.00	16.67	13.33	10.00	26.67	16.67	6.67	26.67	16.67	10.00	30.00	10.00	10.00
Sub_13	23.33	20.00	0.00	16.67	10.00	3.33	16.67	13.33	6.67	16.67	13.33	10.00	20.00	10.00	3.33
Sub_14	23.33	13.33	0.00	20.00	16.67	16.67	20.00	20.00	3.33	13.33	10.00	10.00	30.00	13.33	10.00
Sub_15	13.33	10.00	0.00	10.00	3.33	0.00	13.33	13.33	3.33	23.33	20.00	10.00	13.33	10.00	10.00
Sub_16	20.00	13.33	10.00	23.33	20.00	3.33	20.00	13.33	13.33	23.33	20.00	10.00	16.67	6.67	6.67
Sub_17	20.00	13.33	6.67	16.67	10.00	10.00	16.67	6.67	3.33	26.67	13.33	10.00	23.33	16.67	13.33
Sub_18	20.00	13.33	3.33	13.33	10.00	3.33	16.67	10.00	3.33	20.00	10.00	6.67	30.00	13.33	6.67
Sub_19	23.33	20.00	20.00	13.33	6.67	3.33	20.00	13.33	6.67	13.33	6.67	0.00	20.00	13.33	13.33
Sub_20	16.67	13.33	10.00	20.00	10.00	6.67	16.67	6.67	3.33	16.67	13.33	10.00	23.33	20.00	10.00
Sub_21	16.67	13.33	3.33	16.67	10.00	3.33	13.33	6.67	0.00	30.00	20.00	13.33	10.00	6.67	0.00
Sub_22	20.00	10.00	3.33	16.67	13.33	0.00	26.67	23.33	13.33	20.00	16.67	6.67	23.33	10.00	6.67
Sub_23	16.67	13.33	3.33	16.67	13.33	0.00	20.00	10.00	3.33	16.67	10.00	3.33	23.33	20.00	16.67
Sub_24	16.67	10.00	0.00	13.33	10.00	6.67	23.33	20.00	16.67	16.67	10.00	10.00	16.67	13.33	6.67
Sub_25	20.00	16.67	6.67	23.33	20.00	16.67	20.00	20.00	0.00	23.33	16.67	10.00	16.67	10.00	3.33
Sub_26	20.00	13.33	3.33	23.33	16.67	6.67	10.00	6.67	6.67	20.00	20.00	3.33	26.67	23.33	10.00
Sub_27	16.67	16.67	10.00	23.33	16.67	13.33	16.67	6.67	6.67	10.00	10.00	3.33	16.67	13.33	0.00
Sub_28	23.33	16.67	10.00	6.67	6.67	3.33	20.00	16.67	3.33	13.33	10.00	10.00	13.33	6.67	3.33
Sub_29	20.00	10.00	0.00	20.00	16.67	13.33	16.67	13.33	10.00	23.33	20.00	10.00	13.33	6.67	3.33
Sub_30	20.00	13.33	10.00	10.00	6.67	3.33	26.67	20.00	3.33	16.67	13.33	3.33	20.00	16.67	3.33
Sub_31	23.33	16.67	3.33	16.67	13.33	6.67	26.67	20.00	20.00	16.67	3.33	0.00	16.67	10.00	6.67
Sub_32	23.33	10.00	6.67	23.33	16.67	10.00	23.33	20.00	10.00	30.00	13.33	13.33	10.00	10.00	6.67

Table 4.2 FAR of Subjects in Relaxed State with Varying Threshold

Sub	Entropy			LZ Complx			MPF			SEF			RMS		
	Threshold			Threshold			Threshold			Threshold			Threshold		
	5%	10%	15%	5%	10%	15%	5%	10%	15%	5%	10%	15%	5%	10%	15%
Sub_1	2.90	3.23	8.06	5.16	8.71	12.58	3.87	6.45	13.23	9.68	15.81	26.42	2.90	8.26	13.23
Sub_2	0.00	2.26	4.84	0.00	3.87	9.35	0.32	3.23	3.23	12.26	14.84	17.42	6.45	7.42	12.90
Sub_3	9.68	12.90	18.39	10.00	15.48	20.97	0.32	1.29	1.94	13.23	16.84	18.71	3.23	4.34	12.34
Sub_4	9.68	12.90	18.39	7.74	16.77	21.29	13.87	14.52	20.65	0.65	5.48	8.71	6.45	3.87	5.81
Sub_5	1.29	8.71	11.61	2.90	8.06	12.90	10.97	13.55	19.61	17.10	18.39	18.55	2.58	1.94	13.26
Sub_6	8.39	12.90	17.42	7.74	17.10	21.29	12.34	13.55	19.68	1.29	3.23	9.03	7.10	9.68	11.94
Sub_7	9.68	12.90	18.39	0.97	1.00	4.84	11.45	12.26	12.58	2.26	4.84	6.13	6.13	11.94	16.77
Sub_8	2.26	3.68	7.87	8.06	15.81	19.68	4.84	17.10	24.52	9.35	14.03	16.90	9.40	12.35	15.52
Sub_9	9.68	12.90	18.39	7.74	14.52	19.35	11.29	13.55	18.32	1.61	6.45	8.06	3.23	1.94	7.42
Sub_10	9.47	12.90	18.39	0.97	5.48	9.68	13.87	14.52	18.65	16.13	17.42	21.94	7.10	10.65	15.16
Sub_11	9.68	13.90	18.39	2.90	8.39	12.58	4.84	12.58	14.65	14.52	16.13	16.89	2.97	6.98	12.32
Sub_12	0.00	1.29	4.19	0.65	4.84	7.74	0.65	1.29	2.90	9.35	14.03	16.90	3.23	4.56	8.35
Sub_13	9.68	13.23	19.03	6.45	13.23	20.65	13.87	17.26	19.68	0.97	2.58	5.81	2.34	9.80	13.43
Sub_14	9.68	12.90	18.39	6.45	13.87	18.94	9.03	17.74	19.35	2.65	5.66	6.94	7.10	9.03	11.61
Sub_15	4.84	13.87	20.00	8.06	16.13	19.68	6.77	15.16	21.61	11.94	14.00	16.77	3.45	8.34	12.84
Sub_16	4.19	7.74	14.19	0.65	1.94	2.90	3.87	12.90	18.71	12.26	13.87	15.81	6.13	3.87	5.81
Sub_17	4.52	7.74	14.84	1.94	5.16	13.23	3.97	2.90	3.23	11.61	18.71	19.94	6.13	7.74	13.23
Sub_18	4.52	10.32	14.84	10.65	20.00	21.94	0.97	0.97	1.94	13.23	15.16	17.10	3.23	0.32	2.58
Sub_19	6.13	11.29	19.35	10.00	19.68	21.94	7.42	12.10	13.55	9.03	12.74	19.68	6.13	7.10	15.16
Sub_20	0.65	8.06	12.58	7.10	17.10	21.94	8.06	17.74	23.55	10.97	13.65	16.58	5.43	7.34	12.45
Sub_21	4.84	11.61	20.00	7.10	17.10	21.94	7.74	16.13	22.26	7.74	10.32	13.23	1.94	0.97	4.84
Sub_22	4.52	11.29	19.35	4.52	13.55	17.74	0.97	2.58	7.42	2.26	4.84	6.45	3.12	7.45	18.45
Sub_23	4.52	10.97	15.48	8.06	12.48	15.97	11.29	13.55	16.32	0.32	2.26	6.13	2.34	12.23	15.90
Sub_24	12.26	13.42	17.61	6.13	12.13	16.94	3.23	8.06	12.90	0.32	2.26	5.81	6.77	8.06	12.58
Sub_25	6.13	11.29	17.10	10.94	13.68	17.61	13.87	14.52	18.65	12.68	14.84	16.90	4.23	9.04	14.23
Sub_26	5.48	10.00	15.81	15.48	18.39	20.65	4.61	1.94	5.16	12.32	18.06	21.94	12.23	18.57	18.90
Sub_27	6.13	11.61	18.71	8.06	15.16	21.61	7.10	9.10	13.55	0.00	2.26	4.84	6.45	16.36	19.27
Sub_28	4.84	9.35	11.74	11.94	19.68	21.61	13.87	14.90	19.03	7.74	9.03	12.68	2.90	12.45	15.68
Sub_29	5.16	9.19	16.77	5.16	7.74	12.32	7.10	17.10	19.55	0.65	2.90	5.81	6.13	7.10	15.16
Sub_30	6.13	11.29	17.10	10.00	16.13	20.65	3.23	7.74	12.90	0.32	3.23	8.39	4.23	11.36	13.89
Sub_31	1.94	0.65	4.52	0.00	2.58	10.97	7.42	11.10	13.55	0.65	1.61	6.13	11.00	16.34	24.23
Sub_32	12.26	16.77	19.61	15.48	18.39	20.65	9.68	18.39	22.90	10.65	12.74	14.97	6.77	7.74	12.58

From Table 4.1 and 4.2, it is clear that whenever threshold increases from *lower to higher* (i.e. 5% to 15%), *FRR decreases*, *FAR increases* and *vice versa*. A **threshold level of 10% is optimum for medium security** and was considered for further study.

The mean FRR varied (at 10% threshold) from 13.88% (for LZ Complexity) to 18.69% (for RMS) whereas; mean FAR varies (at 10% threshold) from 13.32% (MPF) to 17.01% (RMS), as shown in Table 4.3.

Table 4.3 Mean FRR and Mean FAR Rates for 32 Subjects at Different Threshold

Feature	Threshold %	FRR	FAR
Entropy	**5%**	19.00	5.97
	10%	16.31	14.10
	15%	8.69	15.35
LZ Complx	**5%**	18.75	6.53
	10%	13.88	15.80
	15%	10.94	16.63
MPF	**5%**	20.63	6.45
	10%	15.25	13.32
	15%	10.63	18.55
SEF	**5%**	19.06	7.37
	10%	16.25	16.26
	15%	9.81	17.36
RMS	**5%**	19.98	13.97
	10%	18.69	17.01
	15%	12.31	18.48

The Genuine Acceptance Rate (GAR) was calculated from FRR as (Kulkarni et al., 2006):

$$GAR = 100 - FRR \text{ in } \% \tag{4.1}$$

Thus, mean GAR for subjects under relaxed condition was 83.69% (Entropy), 86.12% (LZ Complexity), 84.75% (MPF), 83.75% (SEF) and 81.31% (RMS) at 10% security threshold.

4.2.3 Results of Verification in Alcoholic/Controlled Subjects (Dataset 2)

The alcoholic and controlled disposition constituted a total of 30 subjects. In this case as well, the individual FAR and FRR (shown in Table 4.4) were calculated at 10% security threshold for five selected features i.e. Approximate Entropy, LZ Complexity, MPF, SEF and RMS.

Table 4.4 Subjects FAR and FRR under Alcoholic/Controlled Disposition

Subjects	Entropy		LZ Complx		MPF		SEF		RMS	
	FAR%	FRR%	FAR%	FRR%	FAR%	FRR%	FAR%	FRR%	FAR%	FRR%
Sub_1	12.18	13.33	11.83	16.67	12.06	16.67	12.06	16.67	16.32	13.33
Sub_2	9.77	13.33	13.21	20.00	15.51	13.33	12.18	6.67	14.25	16.67
Sub_3	11.60	6.67	21.14	13.33	14.02	13.33	11.15	10.00	10.00	13.33
Sub_4	18.38	13.33	16.66	20.00	12.18	16.67	10.57	16.67	11.03	16.67
Sub_5	13.44	16.67	17.81	10.00	16.89	13.33	2.99	13.33	12.41	13.33
Sub_6	16.89	10.00	12.87	13.33	19.99	16.67	8.39	10.00	10.34	20.00
Sub_7	10.46	16.67	10.92	10.00	18.96	13.33	11.38	16.67	11.95	13.33
Sub_8	12.29	20.00	12.29	13.33	17.81	10.00	18.73	20.00	12.29	16.67
Sub_9	9.42	13.33	10.92	23.33	13.21	10.00	12.29	13.33	6.43	13.33
Sub_10	26.66	16.67	21.95	13.33	13.90	16.67	13.90	13.33	9.77	13.33
Sub_11	8.96	10.00	16.66	16.67	13.10	6.67	15.40	10.00	10.00	20.00
Sub_12	14.48	20.00	13.44	16.67	12.06	10.00	11.03	16.67	11.15	13.33
Sub_13	11.60	16.67	9.77	23.33	9.42	20.00	12.52	16.67	8.96	13.33
Sub_14	18.38	16.67	12.64	13.33	14.02	10.00	16.20	16.67	6.20	13.33
Sub_15	15.51	13.33	11.03	13.33	11.15	10.00	16.32	6.67	8.39	16.67
Sub_16	8.96	13.33	18.50	10.00	17.01	6.67	16.89	10.00	8.96	13.33
Sub_17	19.19	13.33	11.03	6.67	16.66	13.33	5.52	20.00	128.92	16.67
Sub_18	12.29	13.33	18.96	16.67	9.19	13.33	11.60	10.00	16.32	13.33
Sub_19	17.58	16.67	13.21	20.00	14.13	16.67	12.06	13.33	4.60	20.00
Sub_20	13.44	10.00	24.93	16.67	12.06	13.33	8.96	16.67	9.77	13.33
Sub_21	15.51	20.00	13.21	20.00	15.51	13.33	12.06	16.67	11.60	13.33
Sub_22	17.58	16.67	28.84	16.67	12.87	16.67	17.24	13.33	17.24	30.00
Sub_23	10.23	13.33	10.92	20.00	17.01	16.67	15.63	16.67	7.93	16.67
Sub_24	9.19	16.67	12.29	10.00	12.18	13.33	12.41	13.33	9.19	13.33
Sub_25	12.06	10.00	23.21	13.33	19.65	16.67	11.15	10.00	7.01	16.67
Sub_26	8.16	26.67	12.75	13.33	15.63	13.33	23.32	13.33	5.75	13.33
Sub_27	8.04	10.00	20.91	16.67	3.68	13.33	12.52	20.00	9.08	10.00
Sub_28	14.25	13.33	15.28	13.33	12.06	16.67	9.77	10.00	14.02	23.33
Sub_29	17.24	16.67	12.75	13.33	13.21	20.00	1.15	16.67	9.31	16.67
Sub_30	10.46	20.00	14.25	26.67	9.19	20.00	14.48	3.33	11.26	6.67

Refer to Table 4.4, the mean FRR varied from 13.0 (SEF) to as much as 18.93% (LZ Complexity); whereas mean FAR varied from 10.48% (RMS) to 13.87% (MPF). Thus, mean GAR for subjects under alcoholic/controlled disposition condition were 84.93% (Entropy), 81.77% (LZ Complexity), 85.93% (MPF), 87% (SEF) and 81.73% (RMS) at 10% security threshold.

It can be seen from Table 4.1, Table 4.2 and Table 4.4; that the individual features indicated high FAR and FRR during verification. Thus, to overcome this problem the features were normalized and the combination of the features were explored (in the coming sections).

In the next sections, various normalization techniques along with weights were explored to improve the overall accuracy of the system.

4.3 Authentication Module on Normalized Dataset with Assigned Weight

The usage of raw data features resulted in high error rates and hence rectified for suitable recommendations. The raw data were "**normalized**" first with different techniques. Thereafter, to achieve better accuracy, datasets were assigned with some weight vector or "**weights**". The complete steps are explained below (Figure 4.3).

4.3.1 Normalization/Standardization of Database

Normalization minimizes the data redundancy and dependencies. It adjusts the values to a common scale (Aksoy and Haralick, 2000). In this work, two techniques were used for database normalization/standardization as explained below:

(a) Minimum maximum or Min-Max Norm: In this technique of feature scaling, data was scaled in the range of 0 to 1. It is also known as *unity based normalization* and ideal for fewer numbers of observations (Ross and Jain, 2003). Mathematically, it is expressed as:

$$X' = \frac{X - Xmin}{Xmax - Xmin} \tag{4.2}$$

(b) Feature scaling using Unit length (Euclidean norm): The data was scaled to complete vector as unit length. It measures the magnitude of the feature element where feature vectors were divided by the Euclidean distance between feature points (Ross and Jain, 2003). Mathematically, it is expressed as:

$$X' = \frac{X}{//X//} \tag{4.3}$$

Where, $//X//$ denotes Euclidean distance. This technique is mostly used in machine learning process.

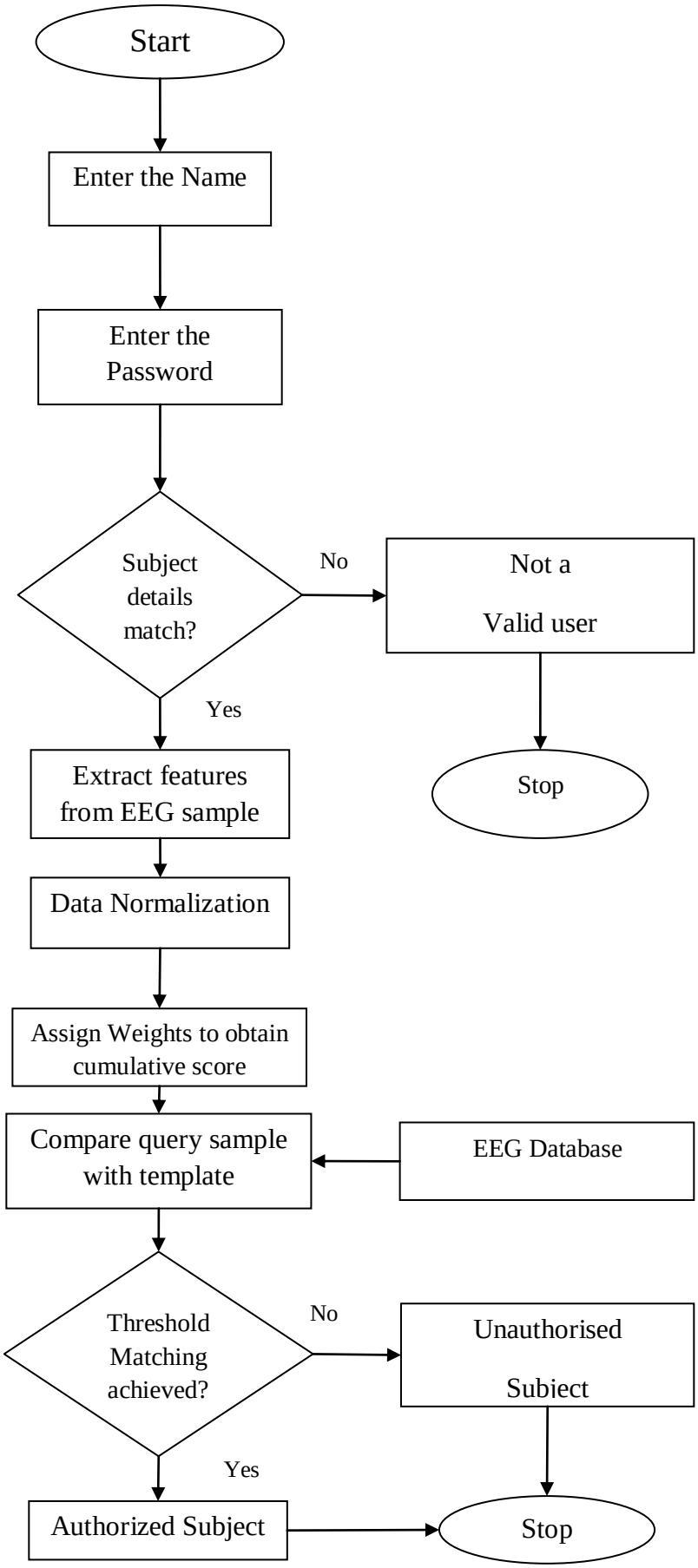

Figure 4.3 Flow Chart of Verification System with Normalization and Weights

The FRR and FAR was calculated for normalized dataset for all the five independent features, as shown in Table 4.5. When compared with error rates of raw dataset for relaxed/alcoholic subjects (Table 4.3 and 4.4), it was observed that FAR got reduced after employment of Normalization techniques; whereas there was hardly any change in FRR rates. The reduced change in FAR (i.e. 3.86% to 7.72% for Min Max Normalization and 2.88% to 9.23% for Euclidean Norm technique) was observed in relaxed state subjects. Similarly, in case of alcoholic/controlled state subjects, reduced FAR i.e. 1.52% to 3.27% for Min Max Normalization and 4.14% to 6.79% for Euclidean Norm has been observed.

Table 4.5 FRR and FAR (mean) for Relaxed and Alcoholic/Controlled Subjects using Normalized Dataset

Relaxed state										
Standrz tech.	Entropy		LZ Complx		MPF		SEF		RMS	
	FRR	FAR	FRR	FAR	FRR	FAR	FRR	FAR	FRR	FAR
Min Max	15.62	10.24	18.12	10.66	15.23	12.35	16.2	8.54	14.37	16.31
Norm	16.25	17.1	11.87	12.92	13.12	13.58	13.75	9.24	18.12	7.78
Controlled/alcoholic state										
Standrz tech.	Entropy		LZ Complx		MPF		SEF		RMS	
	FRR	FAR	FRR	FAR	FRR	FAR	FRR	FAR	FRR	FAR
Min Max	18.23	14.67	14.56	7.34	18.33	14.75	13.22	12.21	15.66	13.77
Norm	18.69	10.93	24	12.14	19.28	9.97	14.23	7.98	18.6	12.66

The results (Table 4.5) still have high FRR and FAR rate. Thus, it was essential to minimize the overall error rates for maximum person recognition. In the next step, the normalized datasets were assigned with weights to give cumulative score.

4.3.2 Assigning Weights to Dataset

Once normalization was over, derived features were assigned with weights to make the proper clustering of sample data for better distinction (Gupta, 2014). In this work, weights were assigned to all feature attributes whose weighted sum equals to one.

$$\sum_{i=1}^{n} Wi = 1 \tag{4.4}$$

The weights were assigned according to **Rank Order Centroid** (ROC) method (Roszkowska, 2013). In this method, the weights are assigned to different features as per their ranking. The method converts the rank into weights with the formula:

$$Wi = \left(\frac{1}{M}\right) \sum_{n=i}^{M} \frac{1}{N} \tag{4.5}$$

Where, M is the number of items and Wi is the weight of the ith item.

The preference or ranks were assigned to feature vector based on relative error rates calculated in the previous section. The features with lower FAR and FRR were assigned higher weights; whereas, feature vectors with higher error rates were assigned lower weights. The weight for relaxed state and alcoholic state subjects is shown in Table 4.6 and 4.7 respectively.

Table 4.6 Ranking and Estimating Weight for Relaxed State Subjects

Feature	**LZ Complexity**	**MPF**	**SEF**	**Entropy**	**RMS**
Ranking	A(1)	B(2)	C(3)	D(4)	E(5)
Finding Weight	0.456	0.256	0.156	0.090	0.042

Table 4.7 Ranking and Estimating Weight for Alcoholic/Controlled State Subjects

Feature	**SEF**	**MPF**	**Entropy**	**RMS**	**LZ Complexity**
Ranking	A(1)	B(2)	C(3)	D(4)	E(5)
Finding Weight	0.456	0.256	0.156	0.090	0.042

4.3.3 Estimating Cumulative Score

Cumulative score was obtained by summation of weighted feature vectors to get a single cumulative score per person and ease of viability in computing performance of the system. The cumulative score was calculates as follows:

Step 1: Normalize the Feature vector with normalization/scaling techniques.

Step 2: The normalized values (Step 1) were multiplied with assigned weight vector.

Step 3: A cumulative score was obtained for *relaxed state subjects and alcoholic/controlled disposition subjects*,

Cumulative Score (CS) = (SEF × W1) + (LZ Complx × W2) + (MPF × W3) +

(RMS × W4) + (Entropy × W5)

Step 4: Similarly, a cumulative score was obtained for other Normalization techniques as well.

4.3.4 Results with Weighted Data

The selected Time and Frequency features (Approximate Entropy, LZ Complexity, MPF, SEF and RMS) for dataset i.e. Relaxed and Alcoholic/Controlled subjects were extracted, normalized and assigned weights. The performance was measured in terms of FAR and FRR error rates from where Genuine Acceptance Rate or True Acceptance Rate can be derived.

4.3.4.1 FAR and FRR for Relaxed State Subjects

The error rates (i.e. FAR and FRR) were measured for relaxed state subjects, where database was normalized, weighted and cumulative score was obtained. The weights were assigned to the database as shown in Table 4.6. The FRR and FAR of subjects (dataset 1) is shown in Figure 4.4 and 4.5 for both normalization technique.

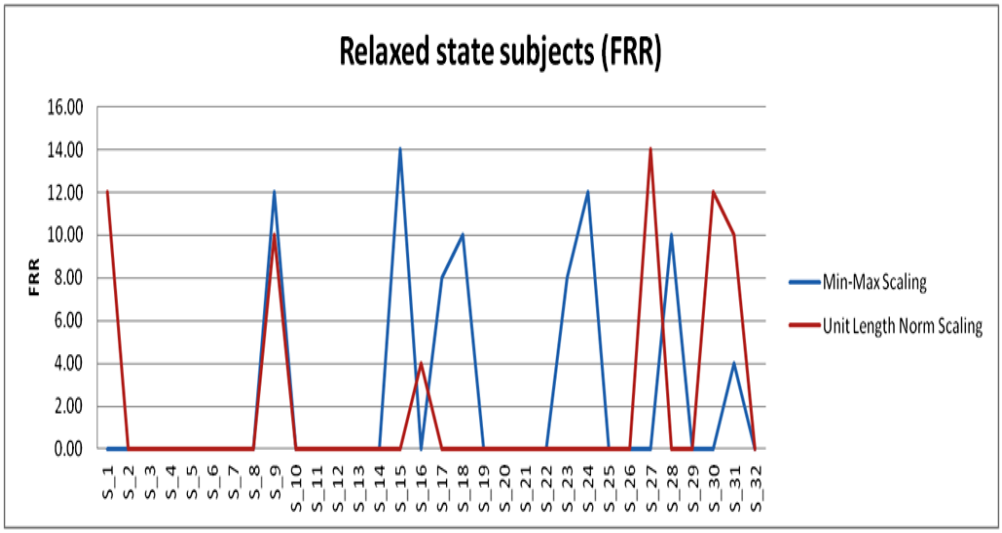

Figure 4.4 FRR for Relaxed State Subjects

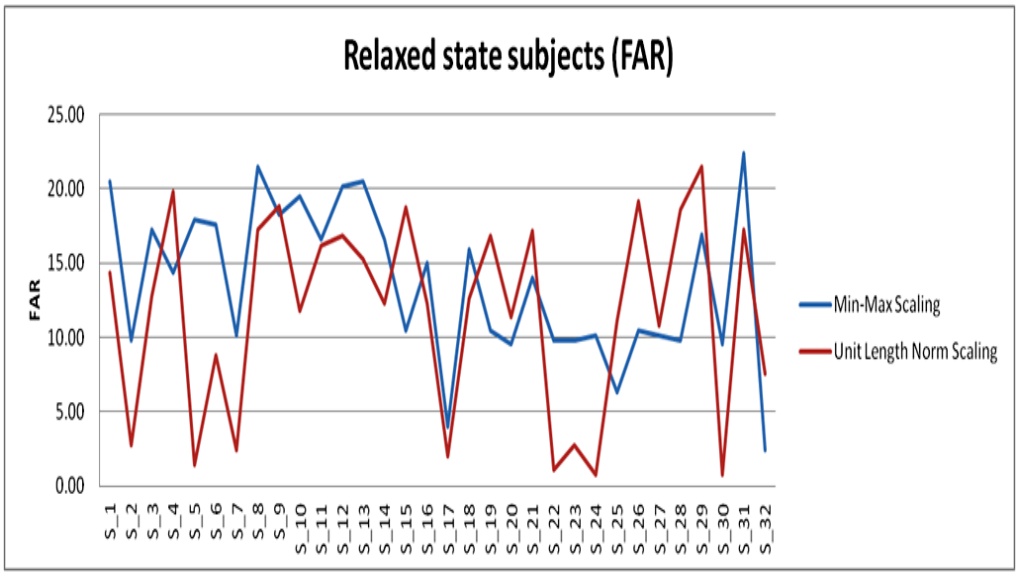

Figure 4.5 FAR for Relaxed State Subjects

Fig 4.4 and 4.5 indicted high GAR (i.e. 91.04%) using Unit length norm technique in comparison to 90.56% of Min-Max scaling technique. The overall results are shown in Table 4.8.

Table 4.8 Error Rates and GAR Comparison for Relaxed State Subjects

Dataset Type	**Norm Technique**	**FRR % (Mean)**	**FAR % (Mean)**	**GAR %**
Relaxed State	Min-Max Scaling	9.44	8.67	90.56
	Unit Length Norm Scaling	8.96	11.67	91.04

The results observed in Table 4.8 was further tested with new weight elements tuned to near proximal values, in order to observe change in overall accuracy of authentication system. The tuned weight elements are shown in Table 4.9 for relaxed state subjects (dataset 1).

Table 4.9 Tuned Weight Elements for Relaxed State Subjects (dataset 1)

Feature	**Relaxed State**		
	Weight (Original)	**Weight_1 (Tuned)**	**Weight_2 (Tuned)**
Entropy	0.090	0.087	0.100
LZ Complexity	0.456	0.451	0.460

MPF	0.256	0.261	0.245
SEF	0.156	0.156	0.150
RMS	0.042	0.045	0.045

The mean FAR and FRR using new weight elements (as shown in Table 4.9) is shown in Table 4.10 for both normalization techniques.

Table 4.10 FAR and FRR with tuned Weight Elements for Dataset-1

	Min Max Scaling			**Unit Length Norm Scaling**		
	FRR % (Mean)	**FAR % (Mean)**	**GAR %**	**FRR % (Mean)**	**FAR % (Mean)**	**GAR %**
Weight_1 (Tuned)	12.93	10.11	87.07	12.45	13.21	87.55
Weight_2 (Tuned)	13.94	15.34	86.06	14.12	19.12	85.88

It can be seen that when weights were altered or tuned to near proximal values, there's increase in error rates and overall decrease in GAR from 90.56% to (86.06%-87.07%) when Min Max scaling was used. Similarly, GAR reduced from 91.04% to (85.88% - 87.55%) using Unit length norm technique. Thus, it was concluded that weights chosen in Table 4.6 has better accuracy and ideal for person verification.

4.3.4.2 FAR and FRR for Alcoholic/Controlled Subjects

The error rates (i.e. FAR and FRR) were measured for Alcoholic/Controlled subjects, where database was normalized, weighted and cumulative score was obtained. The weights were assigned to the database as shown in Table 4.7. The FRR and FAR of subjects (dataset 2) is shown in Figure 4.6 and 4.7 for both normalization technique.

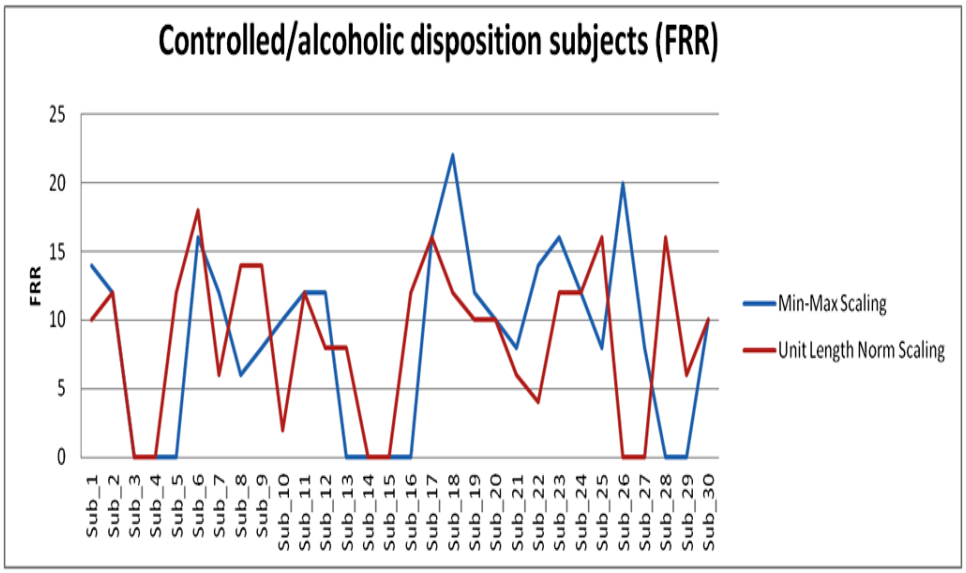

Figure 4.6 FRR for Controlled/Alcoholic Disposition Subjects

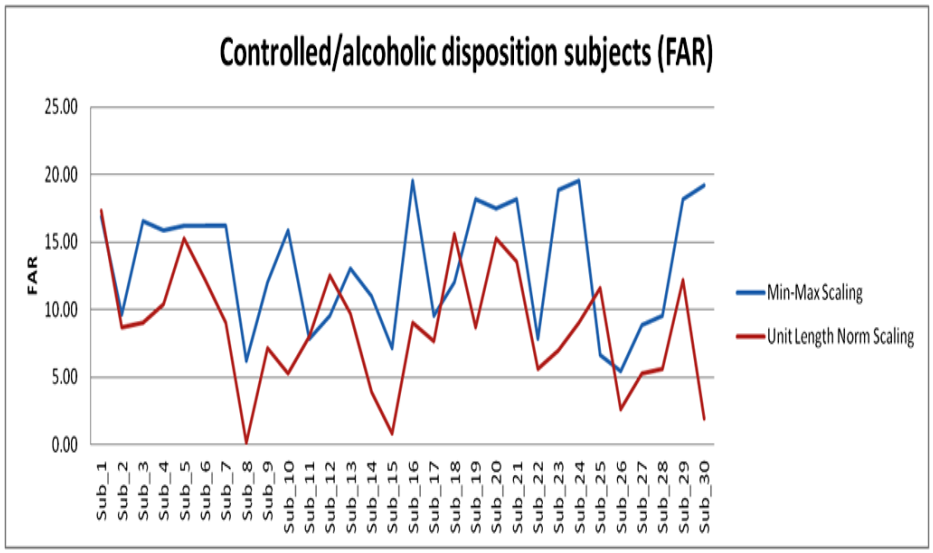

Figure 4.7 FAR for Controlled/Alcoholic Disposition Subjects

The mean FAR and FRR for both normalization techniques is shown in Table 4.11.

Table 4.11 Error Rates and GAR for Controlled/Alcoholic Disposition Subjects

Dataset Type	**Norm Technique**	**FRR % (Mean)**	**FAR % (Mean)**	**GAR %**
Controlled/alcoholic disposition subjects	Min-Max Scaling	8.6	9.2	91.4
	Unit Length Norm Scaling	10.21	12.34	89.79

The results shown in Table 4.11 were further tested with new weight elements tuned to near proximal values to observe any change in accuracy of the system. The tuned weights for alcoholic/controlled subjects (dataset 2) is shown in Table 4.12.

Table 4.12 Tuned Weight Elements for Alcoholic/controlled subjects (dataset 2)

Feature	Relaxed State		
	Weight (Original)	**Weight_1 (Tuned)**	**Weight_2 (Tuned)**
Entropy	0.156	0.155	0.160
LZ Complexity	0.042	0.045	0.040
MPF	0.256	0.250	0.260
SEF	0.456	0.450	0.460
RMS	0.090	0.100	0.080

The mean FAR and FRR using new weight elements is shown in Table 4.13 for both normalization techniques.

Table 4.13 FAR and FRR with tuned Weight Elements for Dataset-2

	Min Max Scaling			**Unit Length Norm Scaling**		
	FRR % (Mean)	**FAR % (Mean)**	**GAR %**	**FRR % (Mean)**	**FAR % (Mean)**	**GAR %**
Weight_1 (Tuned)	13.54	11.2	86.46	13.21	15.21	86.79
Weight_2 (Tuned)	15.21	16.75	84.79	13.69	16.12	86.31

It is evident from Table 4.13 that when weights were altered or tuned to near proximal values, there's increase in error rates and overall decrease in GAR from 91.40% to (84.79%-86.46%) for Min Max technique of scaling. Similarly, there's a decrease in GAR from 89.79% to (86.31% - 86.79%) using Unit length norm technique. Thus, it was concluded that weights chosen in Table 4.7 has better accuracy and ideal for person verification. From the above discussion, it can be concluded that the error rate get minimized with data standardization techniques. The brief comparison between the two is shown in Table 4.11. It is observed that:

(a) There is an improvement in GAR when data was normalized and weights were assigned (as shown in Table 4.14).

(b) Data scaling with unit length normalization (i.e. Euclidean norm) resulted in superior results in comparison to min max normalization.

Table 4.14 Comparison of Results for Relaxed and Controlled/Alcoholic Disposition Subjects

Dataset Type	**GAR (when raw features were used)**	**GAR (when weight vectors were used)**
Relaxed State subjects	81.31% (RMS) to 86.12% (LZ Complexity)	90.56% (Min-Max Scaling) to 91.04% (Unit Length Scaling)
Controlled/alcoholic disposition subjects	81.73% (RMS) to 87% (SEF)	91.4% (Min-Max Scaling) to 89.79% (Unit Length Scaling)

Using the above techniques, it was felt to employ machine learning approach for improvement in system accuracy for subject verification. There are many techniques of machine learning algorithms like Artificial Neural Network (ANN), Linear and Quadratic Classifiers etc. An efficient and robust machine learning algorithm- Support Vector Machine (SVM) for person authentication was employed.

4.4 Authentication Module Using Support Vector Machine (SVM)

Here, authentication was achieved using machine learning algorithm i.e. Support Vector Machine (SVM) for bilinear classification. There are many forms and modalities of SVM. This work employed Radial Basis Function SVM Kernal (RBF-SVM). The overall process is shown in a flow chart (Figure 4.8):

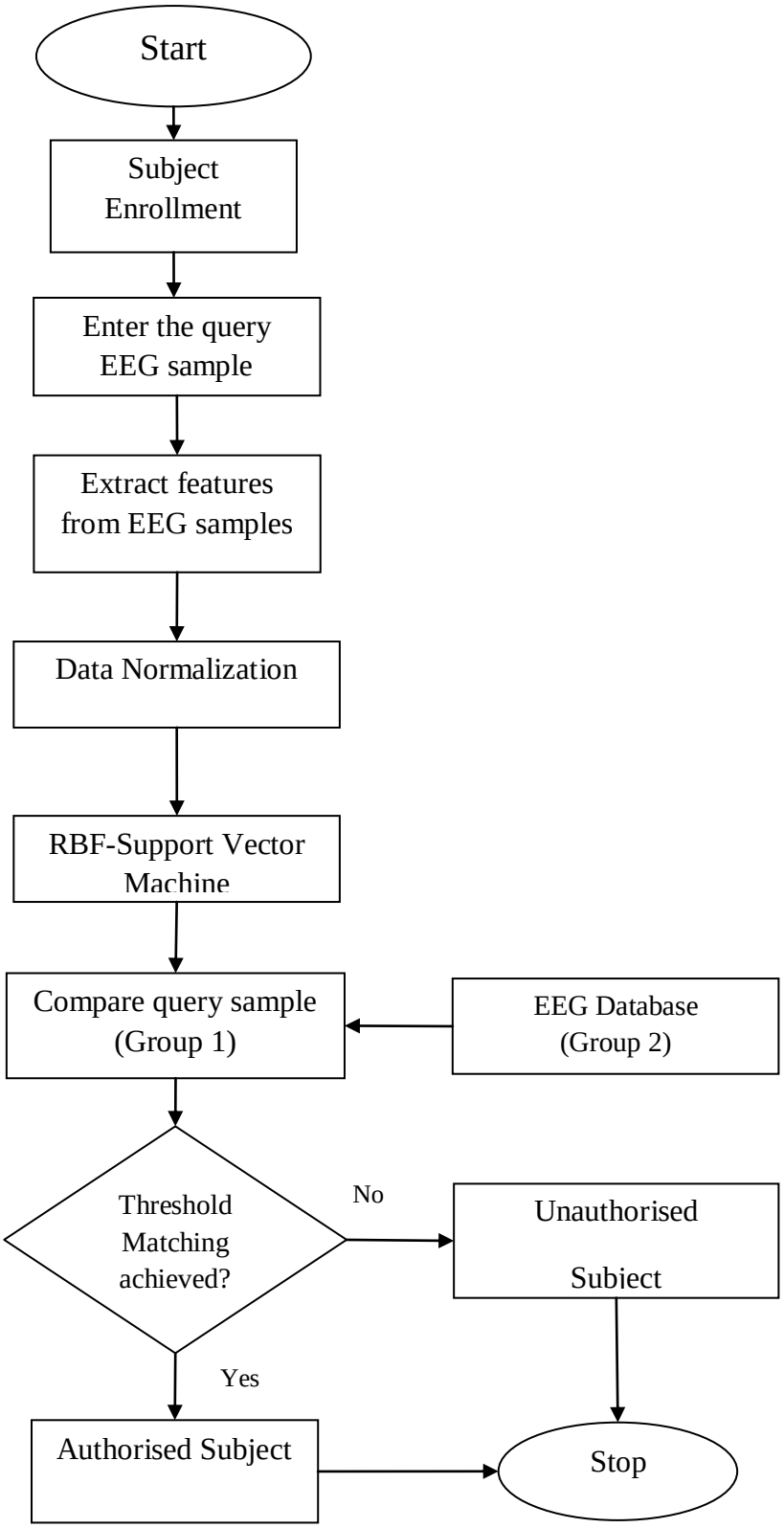

Figure 4.8 Flow Chart for Authentication using SVM Classifier

4.4.1 Radial Basis Function Kernel - Support Vector Machine (RBF-SVM)

Although, Artificial Neural Networks (ANNs) play an important role in pattern recognition, Support Vector Machines (SVMs) have made their presence felt in this regard with its ability to classify higher dimensional data (Gunn, 1998). The primary idea was to revolve around the formation of an optimal hyperplane which perfectly separates multi-dimensional data into binary or multiple classes. In some cases, the data is not easily separable using linear methods. In this situation, SVM plays a significant role by introducing the concept of "kernel induced feature space". In this concept, the data to be analyzed or classified is extended to a higher dimensional space which makes it easily separable (Burges, 1995). Support vector machines belong to the category of kernel based classification methods which possess some innate advantages, like:

- Its ability to generate non-linear decision boundaries using linear classification methods.
- The application of kernel functions enables the users to use it on the data which has no fixed dimensional vector space representation.

SVM training always tries to find the global minimum and its performance depends on the type of kernel selected; where the error penalty parameter is user-defined. The foundations of SVM was developed by Vapnik in 1995 which gained popularity because of its promising features, e.g. better empirical performance. The formulation of SVM is based on Structural Risk Minimization (SRM) principle, which minimizes the upper bound on the expected risk (Schwartz et al., 2006).

For a binary classification problem, if the training data is labelled as $\{x_i, y_i\}, i = 1, \dots, l, y_i \in \{+1, -1\}, x_i \in R^d$. For example, suppose, there is a hyperplane which separates the two classes ("*the separating hyperplane*"). The point x which lie on the hyperplane that satisfies the equation $w.x + b = 0$, where w is normal to the hyperplane. $|b|/_{\|w\|}$ which is the perpendicular distance between the hyperplane to the origin, and $\|w\|$ is the Euclidean norm of w. Let, $d^+ \& d^-$ be the shortest distance from the hyperplane to the nearest positive or negative examples respectively. The margin of the generated hyperplane is defined as $[d^+ + d^-]$. The primary aim of any type of SVM is to find the hyperplane with the largest margin. If we assume that all the training data satisfy the following constraints:

$$x_i.w + b \geq +1, for\ y_i = +1 \tag{4.7}$$

$$x_i.w + b \leq -1, for\ y_i = -1 \tag{4.8}$$

The equations can be combined to form the resulting equation as follows:

$$y_i(x_i.w + b) - 1 \leq 0, \forall\ i \tag{4.9}$$

If the vectors are distributed non-linearly, then it becomes essential to use a kernel function to map the data into a higher dimensional hyperspace wherein a multi-dimensional hyperplane can be used to segregate the data. Kernel functions correspond to an inner product in some expanded hyperspace. Mercer's Theorem states that every semi-positive definite symmetric function is a kernel. The dot product $K_{ij} \equiv K(x_i, x_j)$, represents Gram Matrix (a matrix of dot products in the Euclidean space). Prior to this process, each data point is mapped into the higher dimensional hyperspace via some transformationΦ: $x \rightarrow \varphi(x)$. The quadratic kernel is basically a polynomial kernel of 2nd order; the kernel function is given by:

$$K(x_i, x_j) = (x_i.x_j + 1)^2 \tag{4.10}$$

The radial basis function based kernel is given by:

$K(x^t, x) = exp\left[-\frac{\|x^t - x\|^2}{\sigma^2}\right]$, which defines a spherical kernel whose centre is x^t and σ, which is the user defined radius of the kernel.

4.4.2 Classification with SVM for Person Authentication

The training and testing of data in SVM was done separately in two classes separated by a hyper-plane. Hyper plane differentiates class label and class allocation. The class labels were assigned as "**Label 1** and **Label 2**", as shown in Table 4.15 for a group of 10 subjects. Similar labellings were done for all subject dataset. The labelling is shown in Table 4.15 for subjects between two classes:

- Class 1: The functional group (Labelled as 1)
- Class 2: The residual group (Labelled as 2)

Table 4.15 Labelling of Subjects in Two Different Classes for SVM

Subjects	(Sub 1)	(Sub 2)	(Sub 3)	(Sub 4)	(Sub 5)	(Sub 6)	(Sub 7)	(Sub 8)	(Sub 9)	(Sub 10)
Sub_1	1	2	2	2	2	2	2	2	2	2
Sub_2	2	1	2	2	2	2	2	2	2	2
Sub_3	2	2	1	2	2	2	2	2	2	2
Sub_4	2	2	2	1	2	2	2	2	2	2
Sub_5	2	2	2	2	1	2	2	2	2	2
Sub_6	2	2	2	2	2	1	2	2	2	2
Sub_7	2	2	2	2	2	2	1	2	2	2
Sub_8	2	2	2	2	2	2	2	1	2	2
Sub_9	2	2	2	2	2	2	2	2	1	2
Sub_10	2	2	2	2	2	2	2	2	2	1

4.4.2.1 SVM Classification on Relaxed State Subjects (Dataset 1)

In case of relaxed state subjects, every subject was compared to rest of the subjects by Class label 1 and Class label 2. The class label 1 is subjects own plane whereas, Class label 2 belongs to rest of the data in another plane. The classification accuracy is defined as the probability percentage that a subject from a group of one class is categorised in another class, denoted as **Correct Classification Rate** (CCR). From CCR, False Rejection Rate was determined.

In addition to this, the computation time (in milliseconds) was also recorded to analyze system timing for computation. The results are shown for both normalization techniques applied over the EEG datasets in Table 4.16 to 4.17.

Table 4.16 CCR for Relaxed State Subjects with Min Max Scaling

Subjects	Correct Classification Rate (%)	Error (%)	Computation Time (ms)
Sub_1	97.26	2.74	0.098
Sub_2	97.46	2.54	0.102
Sub_3	97.99	2.01	0.100
Sub_4	97.95	2.05	0.100
Sub_5	97.83	2.17	0.095
Sub_6	96.43	3.57	0.104
Sub_7	97.19	2.81	0.098
Sub_8	97.13	2.87	0.097
Sub_9	97.51	2.49	0.102

Sub_10	98.03	1.97	0.099
Sub_11	97.95	2.05	0.089
Sub_12	97.91	2.09	0.102
Sub_13	96.32	3.68	0.104
Sub_14	97.05	2.95	0.093
Sub_15	97.08	2.92	0.097
Sub_16	97.25	2.75	0.100
Sub_17	98.05	1.95	0.100
Sub_18	97.98	2.02	0.098
Sub_19	97.91	2.09	0.099
Sub_20	96.13	3.87	0.098
Sub_21	97.19	2.81	0.097
Sub_22	97.93	2.07	0.112
Sub_23	97.84	2.16	0.115
Sub_24	98.15	1.85	0.126
Sub_25	98.54	1.46	0.127
Sub_26	97.38	2.62	0.114
Sub_27	95.32	4.68	0.113
Sub_28	97.10	2.90	0.113
Sub_29	97.91	2.09	0.123
Sub_30	97.91	2.09	0.108
Sub_31	98.18	1.82	0.124
Sub_32	98.39	1.61	0.125

Table 4.17 CCR for Relaxed State Subjects with Unit length Euclidean Norm

Subjects	**Correct Classification Rate (%)**	**Error (%)**	**Computation Time (ms)**
Sub_1	97.46	2.54	0.110
Sub_2	95.21	4.79	0.114
Sub_3	96.78	3.22	0.125
Sub_4	97.89	2.11	0.124
Sub_5	97.68	2.32	0.106
Sub_6	98.15	1.85	0.117
Sub_7	98.36	1.64	0.123
Sub_8	97.41	2.59	0.133
Sub_9	94.95	5.05	0.148
Sub_10	94.02	5.98	0.111
Sub_11	96.44	3.56	0.099
Sub_12	94.77	5.23	0.099
Sub_13	91.06	8.94	0.097
Sub_14	93.86	6.14	0.103

Sub_15	97.42	2.58	0.099
Sub_16	94.85	5.15	0.098
Sub_17	95.00	5.00	0.099
Sub_18	96.44	3.56	0.101
Sub_19	95.76	4.24	0.100
Sub_20	92.35	7.65	0.098
Sub_21	94.62	5.38	0.100
Sub_22	96.52	3.48	0.099
Sub_23	93.03	6.97	0.098
Sub_24	94.77	5.23	0.096
Sub_25	94.70	5.30	0.105
Sub_26	96.52	3.48	0.098
Sub_27	94.70	5.30	0.101
Sub_28	94.62	5.38	0.101
Sub_29	95.76	4.24	0.095
Sub_30	91.97	8.03	0.099
Sub_31	95.61	4.39	0.098
Sub_32	97.35	2.65	0.100

From Table 4.16 and 4.17, it was evident that the mean CCR (97.50%) was observed for Min Max Scaling Technique (for dataset 1) with Minimum error rate of 2.49% in comparison to mean CCR of 95.50% for Unit length Euclidean norm at 4.99% errors (Table 4.18). The mean computation time (0.105 ms) was moreover similar for both norm techniques.

Table 4.18 Comparison of CCR for Relaxed State Subjects

Condition	**Scaling Technique**	**Mean CCR (%)**	**Mean Error Rate (%)**	**Mean Computation Time (ms)**
Relaxed State Subjects	Min Max Scaling	97.50	2.49	0.105
	Unit Length Norm (Euclidean)	95.50	4.99	0.106

4.4.2.2 SVM Classification on Alcoholic/Controlled Disposition Subjects (Dataset 2)

In case of Alcoholic/Controlled disposition subjects, the results are shown for dataset normalized with min max scaling and Euclidean norm respectively in Table 4.19 and 4.20:

Table 4.19 CCR for Alcoholic/Controlled Disposition Subjects with Min Max Scaling

Subjects	Correct Classification Rate (%)	Error (%)	Computation Time (ms)
Sub_1	95.83	4.17	0.102
Sub_2	96.82	3.18	0.104
Sub_3	97.56	2.44	0.093
Sub_4	98.07	1.93	0.097
Sub_5	97.14	2.86	0.100
Sub_6	97.86	2.14	0.100
Sub_7	96.91	3.09	0.098
Sub_8	95.64	4.36	0.099
Sub_9	96.99	3.01	0.098
Sub_10	97.51	2.49	0.097
Sub_11	97.41	2.59	0.112
Sub_12	93.98	6.02	0.115
Sub_13	97.84	2.16	0.126
Sub_14	98.04	1.96	0.127
Sub_15	96.15	3.85	0.114
Sub_16	96.98	3.02	0.113
Sub_17	97.58	2.42	0.113
Sub_18	97.21	2.79	0.123
Sub_19	94.06	5.94	0.108
Sub_20	97.83	2.17	0.124
Sub_21	97.93	2.07	0.125
Sub_22	95.96	4.04	0.110
Sub_23	97.05	2.95	0.114
Sub_24	97.62	2.38	0.125
Sub_25	97.17	2.83	0.124
Sub_26	94.24	5.76	0.106
Sub_27	97.65	2.35	0.117
Sub_28	98.14	1.86	0.123
Sub_29	95.91	4.09	0.133
Sub_30	95.76	4.24	0.148

Table 4.20 CCR for Alcoholic/Controlled Disposition Subjects with Euclidean Norm

Subjects	Correct Classification Rate (%)	Error (%)	Computation Time (ms)
Sub_1	93.79	6.21	0.101
Sub_2	94.62	5.38	0.102
Sub_3	95.61	4.39	0.105
Sub_4	94.70	5.30	0.106
Sub_5	93.94	6.06	0.104
Sub_6	97.09	2.91	0.100
Sub_7	97.81	2.19	0.103
Sub_8	97.05	2.95	0.101
Sub_9	97.83	2.17	0.096
Sub_10	96.43	3.57	0.096
Sub_11	97.19	2.81	0.099
Sub_12	97.13	2.87	0.104
Sub_13	98.73	1.27	0.097
Sub_14	98.33	1.67	0.100
Sub_15	95.80	4.20	0.099
Sub_16	97.26	2.74	0.101
Sub_17	97.46	2.54	0.098
Sub_18	97.99	2.01	0.098
Sub_19	97.95	2.05	0.106
Sub_20	93.79	6.21	0.099
Sub_21	94.85	5.15	0.098
Sub_22	96.59	3.41	0.098
Sub_23	95.68	4.32	0.097
Sub_24	93.86	6.14	0.101
Sub_25	96.52	3.48	0.100
Sub_26	95.53	4.47	0.098
Sub_27	94.92	5.08	0.099
Sub_28	93.86	6.14	0.105
Sub_29	96.59	3.41	0.098
Sub_30	97.35	2.65	0.104

From Table 4.19 and 4.20, it was concluded that mean CCR obtained with Min Max Scaling was 96.82% (at 3.17% error) in comparison to 96.20% (at 3.99% error) of Unit length

Euclidean norm scaling. The mean computation time (0.112 ms) was observed, as shown in Table 4.21.

Table 4.21 Comparison of CCR for Alcoholic/Controlled Disposition Subjects

Condition	**Scaling Technique**	**Mean CCR (%)**	**Mean Error Rate (%)**	**Mean Computation Time (ms)**
Alcoholic/Controlled disposition subjects	Min Max Scaling	96.82	3.17	0.112
	Unit Length Norm (Euclidean)	96.20	3.79	0.100

4.5 Authentication on Cognitive/Mental Activity Task (Dataset 3)

This section deals with classification of subjects undergoing mental tasks (dataset 3). Description of various mental tasks has already been discussed in the last chapter. The authentication was achieved for subjects by classification between baseline and combined mental cognitive tasks.

The non-linear features were subjected to two classifiers of SVM i.e. RBF-SVM and Quadratic SVM with 10 fold cross validation scheme. The subjects authentication was carried out using one feature at a time from all channels.

4.5.1 Results using Fractal Dimension

Here, the subject's classification was done using HFD feature as shown in Table 4.22 and 4.23.

Table 4.22 CCR (with Fractal Dimension Features) using R-SVM

		Mental Activity Combination »	**Base, Counting**	**Base, Letter Compo**	**Base, Multiplication**	**Base, Rotation**
R-SVM Classifier (Fractal Dimension)	**Sub_1**	CCR (%)	99	97	95	98
		Time	0.101	0.102	0.105	0.106
	Sub_2	CCR (%)	97	97	96	100
		Time	0.104	0.1	0.103	0.101
	Sub_3	CCR (%)	94	97	95	97
		Time	0.096	0.096	0.099	0.104

		CCR (%)	99	97	98	96
	Sub_4	Time	0.097	0.1	0.099	0.101
		CCR (%)	96	97	98	100
	Sub_5	Time	0.098	0.098	0.106	0.099

Table 4.23 CCR (with Fractal Dimension Features) using Quad-SVM

		Mental Activity Combination	**Base, Counting**	**Base, Letter Compo**	**Base, Multiplication**	**Base, Rotation**
Quad-SVM Classifier (Fractal Dimension)		CCR (%)	99	97	94	98
	Sub_1	Time	0.113	0.134	0.123	0.107
		CCR (%)	96	97	97	100
	Sub_2	Time	0.12	0.579	0.113	0.095
		CCR (%)	95	96	96	96
	Sub_3	Time	0.106	0.128	0.126	0.187
		CCR (%)	100	98	97	95
	Sub_4	Time	0.096	0.153	0.142	0.127
		CCR (%)	98	96	97	99
	Sub_5	Time	0.124	0.121	0.13	0.096

Refer to Table 4.23 and 4.23, it was concluded that the classification accuracy (CCR %) was measured for subjects by comparing the combination of baseline task with cognitive thinking e.g. Subject 1 classification accuracy of 99% when counting activity was considered with reference to baseline. The comparison between the best mental activity along with mean CRR and computation time is shown in Table 4.24.

Table 4.24 Comparison of Cognitive Tasks and Mean CCR

Subjects	**Highest CCR %**	**Best Mental activity**	**Mean CCR %**	**Error %**	**Classifier & Mean computation time (ms)**
Sub_1	99 %	Counting	97.25	2.75	R-SVM (0.104)
Sub_2	100 %	Geometric figure rotation	97.50	2.5	R-SVM (0.102)
Sub_3	97%	Geometric figure rotation & Letter composition	95.75	4.25	R-SVM (0.099)
Sub_4	100 %	Counting	97.50	2.5	Quad-SVM (0.129)
Sub_5	100%	Rotation	97.75	2.25	R-SVM (0.100)

4.5.2 Results using Correlation Dimension

Here, the subject's classification was done using Correlation dimension feature as shown in Table 4.25 and 4.26.

Table 4.25 CCR (with Correlation Dimension) using R-SVM

		Mental Activity Combination	Base, Counting	Base, Letter Compo	Base, Multiplication	Base, Rotation
R-SVM Classifier (Correlation Dimension)	Sub_1	CCR (%)	96	94	96	97
		Time	0.1	0.098	0.103	0.099
	Sub_2	CCR (%)	92	96	97	95
		Time	0.099	0.102	0.099	0.099
	Sub_3	CCR (%)	93	95	96	95
		Time	0.095	0.1	0.099	0.097
	Sub_4	CCR (%)	95	91	95	96
		Time	0.277	0.1	0.112	0.103
	Sub_5	CCR (%)	97	94	95	96
		Time	0.101	0.095	0.1	0.099

Table 4.26 CCR (Correlation Dimension) using Quad-SVM

		Mental Activity Combination	Base, Counting	Base, Letter Compo	Base, Multiplication	Base, Rotation
Quad-SVM Classifier (Correlation Dimension)	S_1	CCR (%)	97	96	97	97
		Time	0.111	0.112	0.109	0.101
	S_2	CCR (%)	94	97	96	94
		Time	0.113	0.115	0.112	0.118
	S_3	CCR (%)	93	96	97	95
		Time	0.106	0.126	0.128	0.117
	S_4	CCR (%)	97	93	95	97
		Time	0.108	0.127	0.129	0.122
	S_5	CCR (%)	97	96	95	96
		Time	0.108	0.114	0.129	0.138

From Table 4.25 and 4.26, it was concluded that highest CCR of 97% was achieved using counting and multiplication activity in comparison to baseline task (as shown in Table 4.27).

Table 4.27 Comparison of Cognitive Task and CCR using Correlation Dimension

Subjects	**Highest CCR %**	**Best Mental activity**	**Mean CCR %**	**Error %**	**Best Classifier & Mean computation time (ms)**
Sub_1	97 %	Counting	95.75	4.25	R-SVM (0.100)
Sub_2	97 %	Multiplication & Letter Compo.	95.25	4.75	R-SVM (0.102)
Sub_3	96%	Multiplication	94.75	5.25	R-SVM (0.097)
Sub_4	97%	Rotation	95.50	4.5	Quad-SVM (0.121)
Sub_5	97%	Counting	95.50	4.5	R-SVM (0.099)

The CCR of 97 % was obtained for many subjects (i.e. subject 1, 2, 4 and 5). The best classifier for Correlation dimension feature was Radial basis function (RBF-SVM) which mean computation time varied from 0.097 to 0.121 ms. The FRR for subject 1 to 5 are 4.25 to to 5.25%. The results shown here are very promising with correct classification rate above 95%

4.6 Summary

The individual's biometric sample was compared or matched with previously enrolled data of that person for verification. Various authentication modules were conducted over a group of subjects i.e. (i) 32 subjects from relaxed state; (ii) 30 subjects from controlled/alcoholic disposition and; (iii) 05 subjects from cognitive task analysis, the details are as follows:

- First of all, the authentication on raw dataset with varying threshold was performed. Threshold range varied from 5%, 10% and 15% i.e. higher to lower security; where *FRR decreased and FAR increased when moving from higher to lower security threshold and vice versa*. An optimum threshold of 10% was selected. In case of relaxed state, the Genuine Acceptance Rate (GAR) varied from 81.31% (RMS) to 86.12% (LZ Complexity); whereas, in case of controlled/alcoholic disposition subjects, the GAR was 81.73% (RMS) to 87% (SEF) when single parameter of EEG signal was considered.

- In order to minimize the error rates and reduce the intra and inter subject variation, **normalization techniques** was employed; where, datasets were normalized with feature scaling techniques (Minimum maximum normalization and Unit length Euclidean norm). The normalization helped in minimizing the FAR rates to certain extent. The scaled data were assigned with **weights** using Rank Order Centroid technique which resulted in 90.56% (Min-Max Scaling) and 91.04% (Unit Length Scaling) in case of relaxed subjects; whereas, 91.4% (Min-Max Scaling) and 89.79% (Unit Length Scaling) for controlled/alcoholic disposition subjects. An improvement was observed in relaxed subject dataset but no significant changes were observed in controlled/alcoholic disposition subjects.
- In addition to conventional techniques for measuring system performance, an efficient and robust machine learning algorithm: Support Vector Machine (SVM) for person authentication was employed. The Correct Classification Rate (CCR) of 97.50% (False rejection error: 2.49%) was obtained for relaxed state subjects. In case of controlled/alcoholic disposition subjects the CCR of 96.82% (False rejection error: 3.17%). The results got improved from 90% to (96.82 – 97.50 %) when machine learning algorithm was employed.
- For cognitive task analysis, non-linear features (Higuchi Fractal Dimension and Correlation dimension) were extracted and were subjected to SVM for classification. Two classifiers were used i.e. Radial Basis Function SVM (RBF-SVM) and Quadratic Support Vector Machine (Quad-SVM). For, HFD, the results were very promising with CCR above 97% (at FRR of 2.25% to 4.25). In case of Correlation dimension, CCR of 95% was obtained (at FRR of 4.25 % to 5.25).

From the above study, we concluded that employing machine learning algorithm (SVM), higher Correct Classification Rate can be achieved, that means, excellent degree of subject verification as compared to threshold techniques. The results are very promising which can be applied as unimodal or multi-modal system biometric system. The robustness of the system can be further improved by fusion of another biometric trait like fingerprint etc. The multi-biometric system using EEG and fingerprint has been discussed in next chapter.

CHAPTER 5

Multimodal Biometric System

Multimodal or multi-biometric system is a combination of more than one biometric modality. Although, EEG can be used as a standalone system. However, EEG has certain limitations like person suffering from rare brain syndrome like Alzheimer's disease, epilepsy etc. would not be able to produce the correct EEG signals every time. Thus, there is a need to combine EEG biometric with robust biometric traits like fingerprint where uniqueness and universality is high. In this chapter, combined biometric using EEG and fingerprint has been discussed for multimodal architecture.

5.1 Drawbacks of EEG Biometric System

Following are the drawbacks of EEG biometric as a unimodal system:

(i) **Challenge to Universality:** An ideal biometric shall possess universal characteristics which should be possessed by each and every person. However, in cases where subject is suffering from rare brain disease like epilepsy, Alzheimer's disease would not be able to produce correct EEG. For such cases, it is advisable to add another biometric identity along with EEG for better person authentication.

(ii) **Challenge to Uniqueness:** Ideally a biometric system shall possess unique feature/identity that has no resemblance to any other person. However, it has been found that in some cases, EEG from monozygotic twins share similar brain wave patterns. Thus, another biometric shall be used in cases of twins for recognition.

(iii) **Interference from Noise:** EEG artefacts whether physiological or extra-physiological, results in noise/errors that creates error. Thus, multi-biometric minimizes the effect of error on overall system design.

The multi biometric system certainly has many advantages over the unimodal system. However, this system is more complex in architecture design, cost and computation time. But this is bearable when question comes of high security concern.

5.2 Multi-Biometric System

The multi-biometric system comprising of Fingerprint and EEG has been proposed in this chapter. The fusion of the two modalities increases the robustness of the system with improved accuracy. Even in cases, when one modality fails or rejects a legitimate user then other one verifies the authenticity.

5.2.1 Choice of Multimodal Biometric Traits

The fingerprint biometric has been selected as second modality along with EEG. The choice of fingerprint is based on the collective characteristics of fingerprint such as high uniqueness, high permanence and universality etc. (Kant and Nath, 2009).

5.2.2 Fingerprint Biometric

In Fingerprint biometric, the fingertip image of a person is taken and stored for matching at later stage. The patterns and geometry of fingerprints are different for different individuals which never changes with growth of a person (Jain et al., 2007). These patterns are hereditary and are formed before birth and never changes throughout the life time. Even in identical twins which share the same DNA have different fingerprints. The specific pattern of a fingerprint like *Whorls, arches and loops* along with patterns of *ridges, furrows and minutiae* are recorded (as shown in Fig. 5.1). These patterns are extracted, processed and stored in template form, and are used whenever a sample is presented for matching.

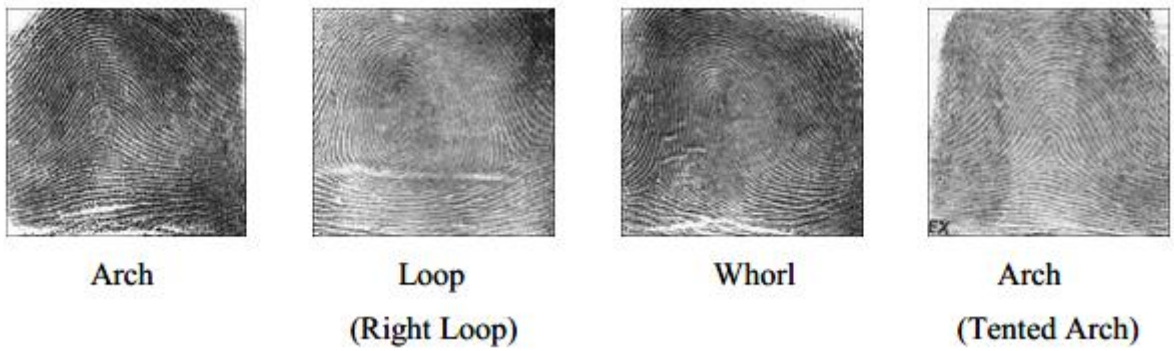

Fig. 5.1 Fingerprint Patterns (Singla, 2010)

Fingerprint authentication is done in two ways: Minutiae based feature authentication and Image based authentication system. Minutiae's are the common micro features indicating bifurcations, islands end points and the centre point of the sweat glands. Whereas, in image

based system, two images are matched and degree of correlation is found between them. Whenever a query sample is presented (either minutiae's or image) for authentication, they are matched with stored template.

5.2.3 Conditions for Combining Biometric Modalities

The process of combining two or more than two modalities is known as Fusion, which can be achieved at sensor, feature, score and decision level (Riera et al., 2009). The various established fusion techniques are: sum rule, tree rule, weighted rule etc. In the present work, *fusion of EEG and fingerprint was done at Matching Score level* using *Fuzzy logic* technique.

The data pertaining to EEG and fingerprint were not available for single user. Thus, for study and experimentation part, left index fingerprint database of 32 subjects were selected from NIST BSSR-Release 1 database (Burr et al., 2006). The fingerprint and EEG matching score of 32 subjects (1st trial) is shown in Table 5.1(a and b) and 5.2 (a and b) respectively.

Table 5.1 (a) Matching Score of Left Index Finger for first 16 Subjects

Sub	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	900	400	600	400	400	200	500	100	100	100	600	100	0	500	300	600
2	100	1000	200	400	100	100	400	100	600	100	100	10	500	600	500	100
3	200	500	930	200	200	500	100	600	700	600	700	100	500	300	800	140
4	200	500	100	970	100	800	100	600	100	200	100	500	500	500	400	200
5	100	500	120	600	900	600	100	100	200	300	500	100	100	400	100	120
6	400	400	60	300	400	1000	100	500	300	600	700	100	500	100	400	300
7	400	300	60	200	500	500	1000	500	100	500	500	100	300	300	400	500
8	200	400	100	200	400	100	200	990	100	100	400	200	500	400	600	150
9	100	200	500	700	100	400	100	600	1000	300	400	600	200	300	100	130
10	10	500	800	400	400	600	600	100	100	1000	300	600	500	300	120	140
11	300	700	700	400	100	100	600	100	500	300	990	300	400	500	400	110
12	90	400	110	300	300	300	500	200	100	100	110	1000	700	500	100	100
13	400	500	120	400	100	200	100	200	120	120	70	700	1000	600	20	200
14	400	400	160	500	200	500	100	300	700	600	200	400	600	1000	600	300
15	600	600	0	600	400	600	100	700	700	600	500	500	100	300	900	400
16	200	400	100	600	600	100	200	400	100	700	100	100	700	600	300	900
17	600	400	40	500	200	100	40	100	50	100	500	300	600	300	200	200
18	70	400	400	500	500	200	60	100	70	800	110	100	300	300	500	300
19	200	300	500	400	40	300	100	600	100	600	700	200	400	300	400	400
20	200	700	400	600	100	700	100	300	200	100	700	500	700	600	600	120
21	200	100	200	400	400	200	200	300	100	500	500	700	500	300	500	60
22	700	300	100	300	200	100	600	700	100	130	600	300	500	400	600	200
23	100	600	60	100	100	70	100	900	500	400	700	100	100	400	300	100
24	100	300	100	200	100	600	600	100	100	200	100	100	100	200	600	400
25	100	500	100	600	600	100	600	200	600	100	200	100	500	500	400	100
26	200	200	600	700	700	40	200	100	100	600	500	600	200	500	100	120

27	200	100	700	400	500	0	500	700	120	400	600	700	600	400	400	100
28	100	80	100	700	800	100	100	100	500	600	600	700	500	300	600	400
29	100	300	120	400	500	100	150	120	500	700	700	500	500	300	400	500
30	700	100	150	500	400	500	100	50	600	600	300	700	100	300	600	500
31	200	400	100	200	400	100	200	100	100	100	400	200	500	400	600	150
32	100	200	500	700	100	400	100	600	100	300	400	600	200	300	100	130

Table 5.1 (b) Matching Score of Left Index Finger for next 16 Subjects

Sub	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**	**31**	**32**
1	300	600	100	600	100	200	500	400	500	190	500	200	500	400	100	100
2	400	100	500	100	400	100	500	70	600	90	600	200	700	100	100	600
3	600	100	500	100	500	90	600	70	600	600	500	100	100	700	600	700
4	500	500	600	120	400	100	600	100	600	600	500	110	100	130	600	100
5	600	500	200	110	600	200	200	100	600	100	400	80	200	200	100	200
6	600	200	400	400	200	500	400	400	100	400	200	600	300	130	500	300
7	300	600	400	400	60	500	500	200	200	600	500	600	400	500	500	100
8	600	600	100	120	500	200	600	100	200	110	500	100	300	400	990	100
9	200	300	600	500	500	400	200	300	300	400	500	400	100	200	600	1000
10	500	100	400	110	100	80	500	400	500	100	400	100	150	200	100	100
11	400	90	200	120	200	100	100	400	100	400	100	110	400	350	100	500
12	400	300	100	100	500	200	100	100	400	340	120	500	40	100	200	100
13	500	100	300	200	300	200	70	100	120	130	400	400	80	400	200	120
14	400	200	400	500	300	300	400	200	300	130	300	400	600	500	300	700
15	500	600	100	300	600	600	500	300	400	700	400	500	600	600	700	700
16	500	100	140	120	600	100	100	100	600	120	100	100	100	100	400	100
17	1000	600	400	100	300	400	500	600	400	110	300	500	130	400	100	50
18	500	1000	400	110	500	500	500	500	600	70	300	500	400	400	100	70
19	300	300	980	400	200	500	100	500	100	400	200	500	120	300	600	100
20	500	200	500	1000	100	500	500	200	600	100	500	100	130	500	300	200
21	400	500	20	600	1000	200	400	500	90	100	400	500	100	500	300	100
22	400	500	200	200	500	990	600	600	70	100	500	300	200	300	700	100
23	500	500	100	500	600	110	900	100	100	500	500	100	600	600	900	500
24	500	300	300	300	400	500	700	1000	100	100	500	400	100	600	100	100
25	500	100	120	400	200	200	500	100	1000	500	200	400	100	100	200	600
26	500	500	500	60	500	400	500	110	200	990	400	100	300	50	100	100
27	500	600	400	60	500	600	200	500	400	500	1000	500	200	40	700	120
28	500	500	600	100	400	600	500	20	300	100	200	980	122	400	100	500
29	700	600	300	200	100	500	100	400	600	600	400	500	1000	100	120	500
30	600	300	300	100	400	400	100	80	100	600	500	400	300	1000	50	600
31	600	600	100	120	500	200	600	100	200	110	500	100	300	400	990	100
32	200	300	600	500	500	400	200	300	300	400	500	400	100	200	200	1000

Table 5.2 (a) Matching Score of EEG for first 16 Subjects

Sub	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	1000	714	767	943	690	853	707	813	591	952	749	70	344	637	736	772
2	599	1000	926	678	967	805	189	861	829	666	951	900	320	892	968	279
3	696	931	1000	769	900	888	314	940	771	758	976	700	160	831	960	398
4	940	757	813	1000	731	904	630	861	627	991	794	194	245	675	780	698
5	551	966	889	633	1000	764	127	822	857	620	915	1000	400	923	933	220
6	827	837	899	893	809	1000	484	953	694	883	878	428	58	747	864	559
7	774	552	593	730	534	660	1000	629	458	736	579	399	719	493	570	950
8	770	878	943	839	849	951	409	1000	728	829	921	547	38	784	906	489
9	309	793	704	405	833	558	186	626	1000	390	734	1500	800	923	755	77
10	950	750	805	991	725	896	642	854	621	1000	786	174	260	669	773	710
11	664	953	976	740	922	861	273	914	790	728	1000	765	212	851	984	359
12	483	345	370	456	333	412	624	393	286	460	362	1000	800	308	356	593
13	604	431	463	570	417	515	781	491	357	575	452	750	1000	385	445	742
14	430	879	796	519	917	661	29	724	929	505	825	125	600	1000	844	72
15	642	969	959	719	937	842	244	896	803	707	983	811	249	865	1000	332
16	814	581	624	768	562	694	948	662	482	775	610	315	652	519	600	1000
17	153	682	584	258	726	425	387	499	908	242	617	182	158	824	640	268
18	242	172	185	228	167	206	312	196	143	230	181	500	400	154	178	297
19	479	915	834	565	951	704	34	764	899	552	862	114	518	968	880	132
20	749	534	574	706	517	638	968	609	443	713	561	450	760	477	551	920
21	338	241	259	319	233	288	437	275	200	322	253	700	560	215	249	415
22	607	433	465	573	419	518	785	493	359	578	455	743	995	387	447	746
23	786	561	603	742	542	670	984	639	465	748	588	373	698	501	579	965
24	68	621	519	177	667	352	498	430	857	160	553	200	120	769	577	373
25	391	852	767	482	890	628	80	693	951	469	796	133	664	975	815	24
26	68	621	519	177	667	352	498	430	857	160	553	200	1200	769	577	373
27	430	879	796	519	917	661	29	724	929	505	825	125	600	1000	844	72
28	446	890	808	533	927	675	9	737	919	520	836	121	574	990	855	91
29	481	916	835	567	952	705	36	765	899	554	863	114	516	968	881	134
30	164	690	593	268	733	435	373	508	914	252	626	180	104	831	648	255
31	68	621	519	177	667	352	498	430	857	160	553	200	120	769	577	373
32	294	782	692	391	823	546	205	614	991	376	723	153	825	913	744	95

Table 5.2 (b) Matching Score of EEG for next 16 Subjects

Sub	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32
1	541	214	115	665	957	353	728	518	622	518	637	643	658	545	518	586
2	759	380	505	129	214	308	217	725	871	725	892	901	922	763	725	821
3	706	340	105	258	185	148	340	675	811	675	831	839	858	711	675	765
4	574	238	907	584	134	254	651	549	659	549	675	682	698	577	549	621

5	785	400	705	65	286	387	156	750	901	750	923	932	954	789	750	850
6	635	284	439	434	146	68	508	607	729	607	747	755	772	639	607	688
7	419	120	292	967	288	726	984	400	481	400	493	498	509	421	400	453
8	666	394	201	357	163	27	434	637	765	637	784	792	810	670	637	721
9	916	500	295	258	300	785	151	875	949	875	923	912	887	921	875	991
10	569	234	946	597	110	270	663	544	653	544	669	676	691	572	544	616
11	723	354	235	216	195	200	301	691	830	691	851	859	879	728	691	783
12	262	0	329	645	571	796	615	250	300	250	308	311	318	263	250	283
13	327	500	279	806	214	995	768	313	375	313	385	388	397	329	313	354
14	850	450	795	97	264	586	2	813	976	813	1000	990	967	855	813	920
15	735	362	327	186	21	237	272	703	844	703	865	874	894	740	703	796
16	441	137	192	913	408	659	964	421	506	421	519	524	536	444	421	477
17	1000	563	350	466	346	1042	350	956	852	956	824	812	785	994	956	917
18	131	920	429	323	714	398	307	125	150	125	154	155	159	132	125	142
19	823	429	991	31	246	505	65	787	945	787	968	978	999	828	787	891
20	405	110	219	1000	214	767	953	388	465	388	477	482	493	408	388	439
21	183	600	896	452	1000	557	430	175	210	175	215	218	223	184	175	198
22	329	513	278	811	205	1000	772	314	377	314	387	391	400	331	314	356
23	426	125	241	950	324	705	1000	407	489	407	501	506	517	428	407	461
24	954	600	705	581	371	1183	459	1000	799	1000	769	757	728	947	1000	867
25	871	466	635	148	275	650	47	833	1000	833	975	965	941	876	833	943
26	954	600	705	581	371	115	459	1000	799	1000	769	757	728	947	1000	867
27	850	450	795	97	264	586	2	813	976	813	1000	990	967	855	813	920
28	842	443	860	76	25	561	22	804	966	804	990	1000	977	847	804	911
29	823	429	995	29	249	503	67	786	944	786	968	977	1000	828	786	891
30	994	560	305	45	342	104	336	950	859	950	831	819	792	1000	950	924
31	954	600	705	58	371	116	459	1000	799	1000	769	757	728	947	1000	867
32	924	506	233	285	145	119	170	883	940	883	913	903	877	929	883	1000

5.3 Fuzzy logic for Biometric Fusion

Fuzzy logic is a computational technique that decides intermediate values within the range of definite evaluations like true/false, yes/no etc. (Zadeh, 1965).

5.3.1 Introduction to Fuzzy Logic

The concept of Fuzzy logic was introduced by Lotfi Zadeh in the year 1965 (Zadeh, 1965, 1968 and 1984). The fuzzy logic models (also known as fuzzy inference systems) are constituted of numerous “if-then” rules. For example, Figure 5.2 shows the triangular fuzzy inference of room temperature.

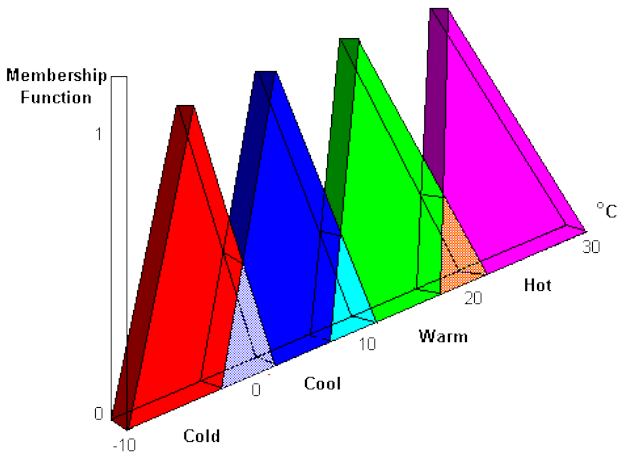

Fig 5.2 Fuzzy Inference System for Measurement of Room Temperature

Fuzzy logic have the following advantages over conventional techniques (Zadeh, 1984)

- It provides a flexible system in rule based decisions which is easy to comprehend.
- Fuzzy logic is tolerant of imprecise data.
- Nonlinear functions of arbitrarily complex system can be modelled using fuzzy logic.
- It can be blended with conventional techniques.
- Easy to program and user friendly programming language.

5.3.2 Fuzzy Set Operations

(i) Universe of Discourse

It is the range of all possible values that define the input and output variable for fuzzy setup. The input variable is EEG and fingerprint whereas; output variable is decision of authentication i.e. acceptance, rejection and re-enter (Figure 5.3). The range of universe of discourse for input and output is shown in Table 5.3.

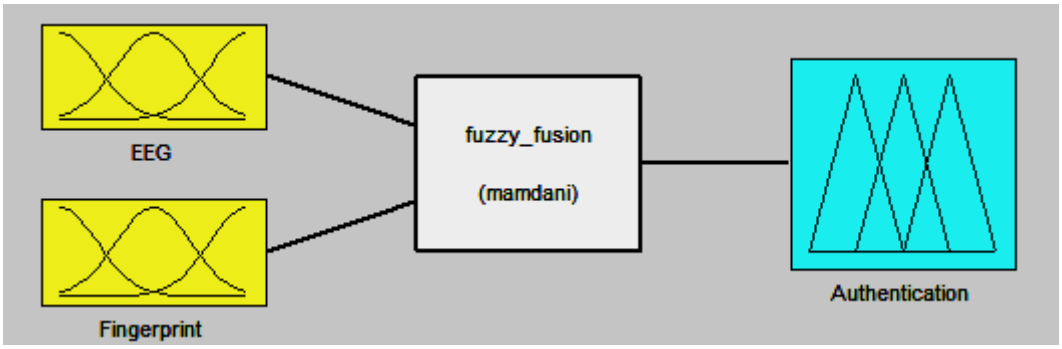

Fig 5.3 Input and Output description in Fuzzy Logic Fusion

Table 5.3 Universe of Discourse for Input and Output Variable

Modality	Input/Output	Minimum Value	Maximum value
EEG	Input	0	1000
Fingerprint	Input	0	1000
Authentication	Output	0	1000

(ii) Assigning Fuzzy Membership function for Input

The range of crisp value for Input (EEG and Fingerprint) is 0 to 1000. Four fuzzy variables were selected i.e. low, medium, high and very high. The fuzzy membership functions for input variable for EEG and fingerprint are shown in Table 5.4. Fig. 5.4 and Fig. 5.5 represent the pictorial representation of the membership function of EEG and Fingerprint respectively.

Table 5.4 Fuzzy Range and Membership Function for Input Variable i.e. EEG and Fingerprint

Fuzzy Type	Crisp range	Membership Function
Low	0-500	Trapezoidal
Medium	300-700	Triangular
High	500-800	Triangular
Very High	700-1000	Trapezoidal

The fuzzy membership for input variable is shown in Figure 5.4 (for EEG) and Figure 5.5 (for fingerprint) below:

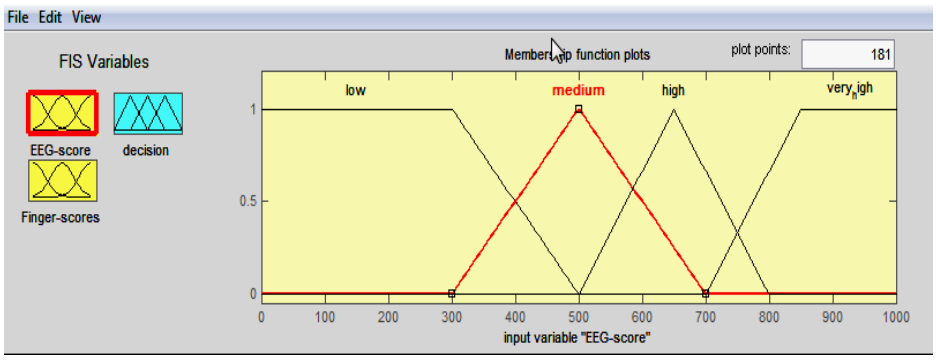

Fig 5.4 Membership Function for EEG Score

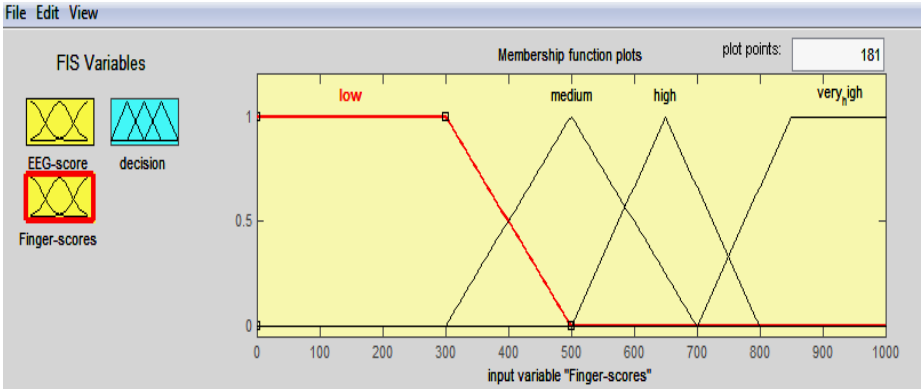

Fig 5.5 Membership Function for Fingerprint Score

(iii) Assigning Fuzzy Membership function for Output

The range of crisp value for Input (EEG and Fingerprint) is 0 to 1000. Similarly, in case of output (authentication claim) the crisp range is 0 to 1000. Three fuzzy variables were selected on the basis of authentication module i.e. Accept, Reject and Reenter. The fuzzy membership function for output variable with different authentication levels is shown in Table 5.5 and fuzzy membership for output variable is shown in Figure 5.6.

Table 5.5 Fuzzy Range and Membership Function for Output Variable i.e. Authentication Claim

Fuzzy Type	**Crisp range**	**Membership Function**
Reject	0-600	Trapezoidal
Reenter	500-700	Triangular
Accept	650-1000	Trapezoidal

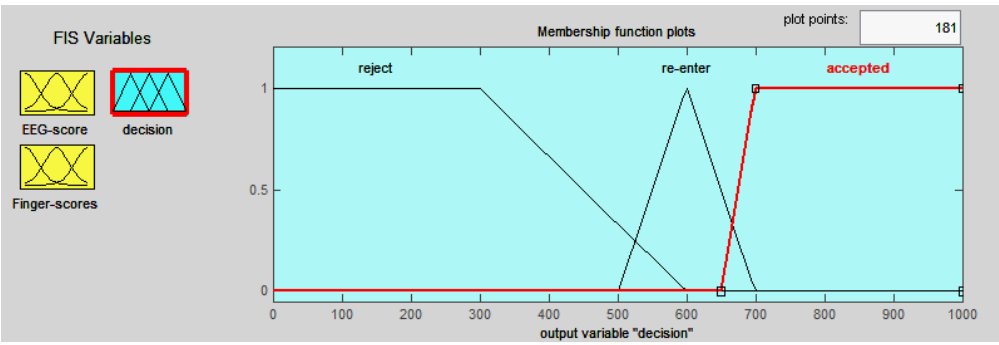

Fig 5.6 Membership Function for Output Variable (Authentication Claim)

(iv) Fuzzy Rule base

In fuzzy logic system, a rule base controls the output based on provided input. The rules are based on "If-Then" conditional statement. For example, the statement and output is stated as:

- IF (EEG is High) AND (Fingerprint is Low), THEN command is to "Reject"
- IF (EEG is High) AND (Fingerprint is Medium), THEN command is to "Accept"

There are two logical operators in Fuzzy logic system: **AND** and **OR**. In this study, AND logical operator has been used.

(v) Implications

Fuzzy implications are the inferences obtained when logical operations on input and output variable are used. It provides the evidence of belief or disbelief on conclusion. Clipping (min) and Scaling (prod) are the two methods of implications. In this work clipping (min) has been used for implication.

(vi) Aggregation and Defuzzification of output

Aggregation is the process where results of output variable are combined into a single fuzzy set. Fuzzy logic constitutes three aggregation techniques i.e. maximum (max), summation (sum) and probabilistic (probor). The "max" aggregation technique has been used in this work.

After aggregation, defuzzification of output is done. It is the process where fuzzy inferences are assigned a crisp number. Fuzzy logic has many defuzzification methods like centroid, bisector, center of sums etc. In this work, centroid defuzzification technique has been used.

5.3.3 Rules for Security System

The rules have been framed for multi-biometric security system using EEG and Fingerprint. The rules are formulated in such a way that if one input variable is very high and other one is also high then the user will be "accepted". In another case, if one input is of medium category and other of low then the output will be "reenter" and subject has to be

enrolled once again. Similarly, if both input variables are low or very low then the output will be “rejected” and person will be unauthorised by the system.

On the basis of above criterion, rules have been frames as follows:

1. If (EEG-score is low) and (Finger-scores is low) then (decision is reject) (1)
2. If (EEG-score is low) and (Finger-scores is medium) then (decision is reject) (1)
3. If (EEG-score is low) and (Finger-scores is high) then (decision is re-enter) (1)
4. If (EEG-score is low) and (Finger-scores is very_high) then (decision is accepted) (1)
5. If (EEG-score is medium) and (Finger-scores is low) then (decision is reject) (1)
6. If (EEG-score is medium) and (Finger-scores is medium) then (decision is re-enter) (1)
7. If (EEG-score is medium) and (Finger-scores is high) then (decision is accepted) (1)
8. If (EEG-score is medium) and (Finger-scores is very_high) then (decision is accepted) (1)
9. If (EEG-score is high) and (Finger-scores is low) then (decision is reject) (1)
10. If (EEG-score is high) and (Finger-scores is medium) then (decision is accepted) (1)
11. If (EEG-score is high) and (Finger-scores is high) then (decision is accepted) (1)
12. If (EEG-score is high) and (Finger-scores is very_high) then (decision is accepted) (1)
13. If (EEG-score is very_high) and (Finger-scores is low) then (decision is re-enter) (1)
14. If (EEG-score is very_high) and (Finger-scores is medium) then (decision is accepted) (1)
15. If (EEG-score is very_high) and (Finger-scores is high) then (decision is accepted) (1)
16. If (EEG-score is very_high) and (Finger-scores is very_high) then (decision is accepted) (1)

The graphical presentation for rule base and surface view for the given input and output is shown in Figure 5.7 and Figure 5.8.

Fig 5.7 Rule Base for Input and Output Variable

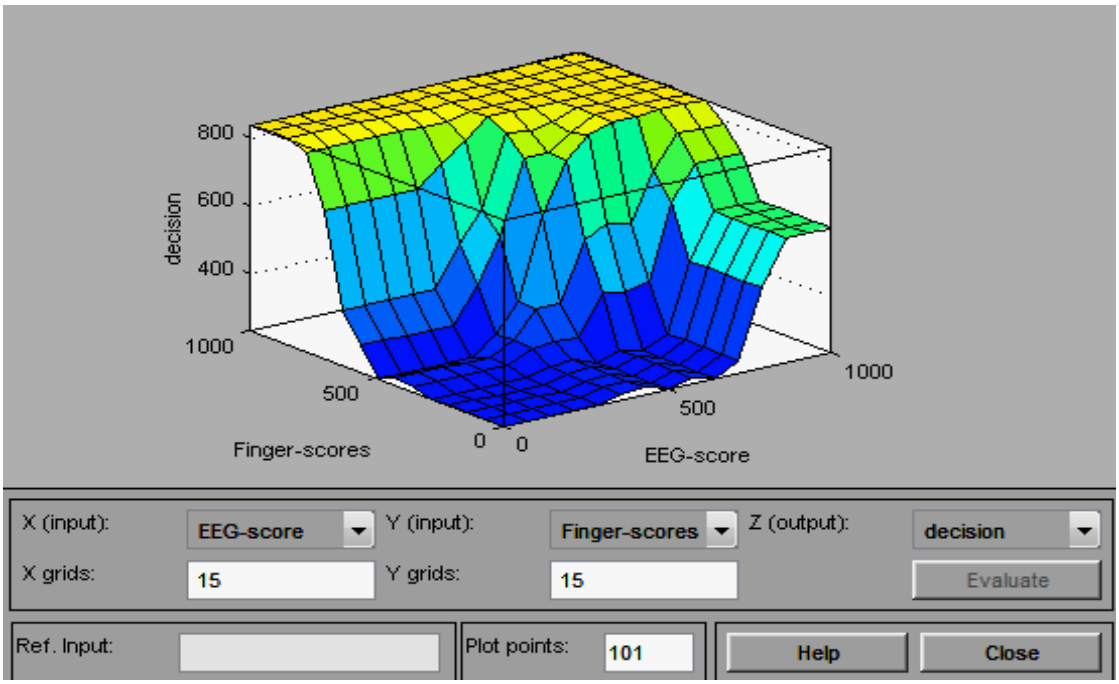

Fig 5.8 Surface Graph for Input and Output Variable

The Fuzzy program was executed on 32 subject's EEG and Fingerprint matching score. On the basis of fuzzy decisions and rule base, the following results were obtained (Table 5.6 a, b). The results of fusion has been shown as Accepted (denoted as A), Rejected (denoted as R) and Re-enter (denotes as RE) in Table 5.6.

Table 5.6 (a) Output based on Fusion of EEG and Fingerprint for first 16 subjects

Sub	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
1	**A**	R	R	R	R	R	A	R	R	R	R	R	R	RE	R	RE
2	R	**A**	R	R	R	R	R	R	R	R	R	R	R	A	R	R
3	R	R	**A**	R	R	R	R	R	A	R	RE	R	R	RE	R	R
4	R	R	R	**A**	R	RE	R	A	R	R	R	R	R	R	R	R
5	R	RE	R	RE	**A**	R	R	R	R	R	A	R	R	R	R	R
6	A	R	R	R	A	**A**	R	R	R	A	A	R	R	R	R	R
7	RE	R	R	R	R	RE	**A**	R	R	R	RE	R	R	R	R	R
8	R	RE	R	R	RE	R	R	**A**	R	R	R	R	R	R	A	R
9	R	R	R	RE	R	R	R	RE	**A**	R	R	R	R	R	R	R
10	R	R	R	R	R	R	R	R	R	**A**	R	R	R	R	R	R
11	R	R	RE	R	R	R	R	R	RE	R	**A**	R	R	R	R	R
12	R	R	R	R	R	R	RE	R	R	R	R	**A**	A	R	R	R
13	R	R	R	R	R	R	R	R	R	R	R	RE	**A**	R	R	R
14	R	R	R	R	R	R	R	R	R	R	R	R	R	**A**	RE	R
15	R	R	A	R	R	R	R	R	RE	RE	RE	R	R	R	**A**	R
16	R	R	R	R	A	R	R	R	R	RE	R	R	R	RE	R	**A**
17	R	R	R	R	R	A	R	A	R	R	R	R	R	R	R	R
18	R	R	R	R	R	R	A	R	R	R	R	R	R	R	R	R
19	R	R	RE	R	R	R	R	R	R	R	R	R	R	R	RE	R
20	R	R	R	R	R	R	R	R	R	R	A	R	R	RE	R	R
21	R	R	R	R	R	R	R	R	R	R	R	R	RE	R	R	R
22	A	R	R	R	R	R	R	R	R	R	R	R	RE	R	R	R
23	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R
24	R	R	R	A	R	R	R	R	R	R	R	R	R	R	R	R
25	R	R	R	R	R	R	R	R	R	R	R	R	R	A	R	R
26	R	R	A	R	R	R	R	R	A	R	R	R	R	R	R	R
27	R	R	R	R	R	R	R	R	R	R	R	R	R	R	RE	R
28	R	R	R	RE	R	R	R	R	R	R	R	R	R	R	A	R
29	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R
30	R	R	R	R	R	R	R	A	R	R	R	R	R	R	R	R
31	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R
32	R	R	RE	R	R	R	R	RE	R	R	R	R	R	R	R	R

Table 5.6 (b) Output based on Fusion of EEG and Fingerprint for next 16 subjects

Sub	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**	**31**	**32**
1	R	R	R	R	R	R	A	R	RE	R	RE	R	RE	R	R	R
2	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R
3	RE	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R
4	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R
5	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R

6	R	R	R	R	R	R	R	R	R	R	R	A	R	R	R	R
7	R	R	R	R	R	A	R	R	R	R	R	A	R	R	R	R
8	RE	R	R	R	R	R	R	R	R	R	RE	R	R	R	R	R
9	R	R	R	R	R	R	R	R	R	RE	RE	RE	R	R	RE	R
10	R	R	R	R	R	R	RE	R	R	R	R	R	R	R	R	R
11	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	RE
12	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R
13	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R
14	A	R	A	R	R	R	R	R	R	R	R	R	R	A	R	R
15	A	R	R	R	R	R	R	R	RE	A	R	R	R	R	A	R
16	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R
17	**A**	R	R	R	R	R	R	RE	R	R	R	R	R	R	R	R
18	R	**A**	R	R	R	R	R	RE	R	R	R	R	R	R	R	R
19	R	R	**A**	R	R	R	R	A	R	R	R	RE	R	R	R	R
20	R	R	R	**A**	R	R	R	R	R	R	R	R	R	R	R	R
21	R	A	R	R	**R**	R	R	R	R	R	R	R	R	R	R	R
22	R	R	R	R	R	**A**	RE	R	R	R	R	R	R	R	R	R
23	R	R	R	RE	R	R	**A**	R	R	R	R	R	R	R	RE	R
24	R	R	R	R	R	R	R	**A**	R	R	R	R	R	A	R	R
25	R	R	R	R	R	R	R	R	**A**	RE	R	R	R	R	R	R
26	R	R	R	R	R	R	R	R	R	**RE**	R	R	R	R	R	R
27	R	R	RE	R	R	R	R	R	R	R	**A**	R	R	R	RE	R
28	R	R	A	R	R	R	R	R	R	R	R	**A**	R	RE	R	RE
29	R	R	R	R	R	R	R	R	A	R	R	R	**A**	R	R	RE
30	RE	R	R	R	A	R	R	R	R	R	R	RE	R	**A**	R	R
31	RE	R	R	R	RE	R	R	R	R	R	RE	R	R	R	**A**	R
32	R	R	R	R	R	R	R	R	R	R	A	R	R	R	R	**A**

** A-Accepted, R-Reject, RE-Re-enter

The fusion results shown in Table 5.6 (a and b) are iterated on 1st trial of EEG and fingerprint sample. For remaining trials i.e. 29, the consolidated FRR and FAR is shown in Table 5.7.

Table 5.7 Consolidated FRR and FAR using Fuzzy Logic

	FRR	**FAR**
Samples Rejected/Samples falsely accepted	22	694
Total Sample Size	320	9920
Total %	6.8	7

From the above results, it was concluded that FRR and FAR was considerably lowered down when multi-biometric approach was employed with overall Genuine Acceptance Rate of 93.2% at FAR of 7%.

5.4 Summary

This chapter discusses the limitations of EEG as uni-modal biometric system. In this work, fingerprint biometric has been selected (because of its high level of uniqueness, permanence and performance) as a second biometric modality along with EEG. Fingerprint database from left index finger (NIST BSSR1) database was selected for fusion with EEG dataset at *score level* of fusion for 32 subject biometric sample.

The fusion of the two modalities was done using Fuzzy logic technique. The fuzzy inference system was built with 16 “if-then” rules. Two input i.e. EEG and Fingerprint and one output i.e. claim of authentication were selected with crisp range of 0 to 1000. The overall GAR of 93.2% at FAR of 7% was achieved using EEG and fingerprint biometric.

CHAPTER 6

Conclusion and Future Scope

In the present thesis, the efforts were made to develop biometric verification algorithm using EEG in order to counteract shortcomings of conventional and emerging biometrics. The outcome of work is presented in this chapter along with the future scope in this area.

6.1 Conclusions

The conclusions of the work are being presented (point wise) as follows:

- The EEG data acquisition was a cumbersome task because of placement of multiple electrodes over the scalp with gel. Instead of positioning 128 channels, that makes the task uneasy and time consuming for subjects, EEG was acquired from specific location of the brain i.e. Parietal and Occipital region of brain (because, these regions reflect high alpha rhythmic activity which is responsible for genetic specificity). Thus, only 2-channel system was employed and electrodes were pasted with no time frill, making the recording procedure easy and accurate. It was observed that EEG rhythm from parietal region of brain provides information about perception.
- A novel method of artefact elimination was implemented that are highly embedded inside the EEG like Electrooculogram. To remove such artefacts Fast Independent Component Analysis (FastICA), a multivariate signal statistical technique was used for decomposing the signals into their independent components. This technique effectively removed the EEG and Noise signal separately into independent components based on their Negentropy. An improved signal to noise ratio was obtained by this process.
- It was observed that RMS, Approximate entropy, Lempel-Ziv complexity, Median Power Frequency and Spectral Edge Frequency features of Linear technique indicated less intra class and maximum inter class variation. These features from the Linear technique were found to be ideal for biometric matching.
- The authentication using individual features resulted in maximum GAR of 86.12% (LZ Complexity) for dataset type 1; and 87% (SEF) for dataset type 2. However, when the features were combined in a definite proportion using rank order centroid

method, accuracy was increased to 91.04% for dataset type 1 and 91.40% for dataset type 2. Therefore, combination of different selected features must be used for authentication.

- There was an improvement in Correct Classification Rate (CCR) when EEG features were tested with machine learning approach i.e. Support Vector Machine. The overall accuracy improved and error rates decreased in person recognition. The SVMs are used for inter related combination of task which enables bilinear classification between baseline task and cognitive thinking. It was observed that Multiplication and visual counting task has better impact on subject classification.
- The drawbacks of the EEG unimodal system have been rectified by combining EEG with Fingerprint for multimodal biometric system. The fusion of the two modalities were done by Fuzzy logic technique at score level which leads to an improvement of 6.8% Genuine Acceptance rate and FAR of 7%.

6.2 Scope for Future Work

From the research work presented in this thesis, the following are recommended for further investigation and future work:

- The task was performed on 67 subjects. The investigations on more subjects with increased number of trials may likely improve the overall accuracy of the system.
- The current work was carried out on subjects with Eyes open, Stimuli response and Cognitive task abilities. The new variants of stimuli or emotional state like sleep, stress etc. could be explored to find the task more suitable and robust for EEG Biometrics.
- In the future, the effect of ageing and other mental ailments may be explored on biometric verification.
- The current work is based on verification system; in our next approach it would be attempted to develop subject identification system using EEG.
- The fusion was achieved using fingerprint which can further be explored with other biometric traits like ECG, Voice etc. to find higher reliability over the time.

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