MULTIMODAL HYBRID BIOMETRIC IDENTIFICATION USING FACIAL AND ELECTROCARDIOGRAM FEATURES

A DISSERTATION

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OF

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CANDIDATE'S DECLARATION

I, **Naveen Kumar, Roll No. 2K15/SPD/501**, student of **M. Tech.** (Signal Processing and Digital Design), hereby declare that the project Dissertation titled "**Multimodal Hybrid Biometric Identification using Facial and Electrocardiogram Features**", which is submitted by me to the Department of Electronics and Communication Engineering, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology, is original and not copied from any source without proper citation. This work has not previously formed the basis for the award of any Degree, Diploma Associateship, Fellowship or other similar title or recognition.

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CERTIFICATE

I, hereby certify that the Project Dissertation titled "**Multimodal Hybrid Biometric Identification using Facial and Electrocardiogram Features**", which is submitted by **Naveen Kumar, Roll No. 2K15/SPD/501**, Electronics and Communication Engineering, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology, is a record of the project work carried out by the students under my supervision. To the best of my knowledge this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

Place: Delhi

Date: 26/6/2018

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ABSTRACT

A single biometric is always prone to errors and misleading results. The inclination has been towards employing two or more biometric traits for designing any schema, accomplishing a superior efficiency. As per the application, these schemas can be deployed for identification as well for recognition, proving to be instrumental in multitudinal fields. Biometric traits examined in the proposed schema are electrocardiogram and face traits. For the face traits, endeavour has been put for entropy biased identification, employing DCT before PPCA. Further exploration of Electrocardiogram signal has been compassed, including the diverse feature points and classifiers. Fiducial points and temporal locale of these points, combined with entire PQRST segment, prove to be an enriching feature set, resulting in much improved results. The score level fusion is exercised along with normalization. The novel fusion schema worked for these two biometric traits does not put any bias on any the traits but works to add the end outputs of the two separate schemas, such as they are employed independently, the best of which is selected as end identification of personal. The schema is certified using the Yale facial dataset and ECG-ID set from Physionet.

This addition has shown tremendous enrichment to our accuracy results, strengthening our methodology.

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LIST OF SYMBOLS, ABBREVIATIONS

ECG	Electrocardiogram
PLI	Power Line Interference
ANN	Artificial Neural Network
SVM	Support Vector Machine
CM	Contribution Map
ID	Identity
KNN	K-nearest neighbors
NN	Neural Network
PCA	Principal Component Analysis
FLDA	Fisher’s Linear Discriminant Analysis
FAR	False Acceptance Rate
FRR	False Rejection Rate
DCT	Discrete Cosine Transform
PPCA	Patch Principal Component Analysis
EM	Entropy Map
BW	Baseline Wander
LPF	Low Pass Filter
HPF	High Pass Filter
STFT	Short Time Fourier Transform
FT	Fourier Transform
WT	Wavelet Transform
CWT	Continuous Wavelet Transform

DWT	Discrete Wavelet Transform
FFT	Fast Fourier Transform
FIR	Finite Impulse Response
IIR	Infinite Impulse Response
dB	Duabechies
AC	Approximation Coefficients
RBFN	Radial Basis Function Network
SF	Score Fusion
PM	Probabilistic Model
CA	Classification Accuracy
OA	Overall Accuracy
EWPPCA	Entropy Weighed Patch Principal Component Analysis

CHAPTER 1

INTRODUCTION

Accurate and motorized identity authentication and validation has become one of the indispensable facet of our everyday lives. Biometric is predominantly affiliated to living beings, where every living being has divergent bundle of these traits, typically concealing fingerprint, retina, face, heart sound, iris etc. Identity defrauding related liabilities are invoked as security entanglements by long-established recognition mechanisms like ID cards/tokens and Pin/Password details.

There are two parts of a security schema - first is identification, which caters to a personal determination of legitimate user identity, and second is authentication, direction of which is to certify claimed identity of the personal. The context in which the security schema is installed concludes the level of acceptance of the system, an army facility or a supremely impregnable government/private zones or enterprise has a very eminent security rank and hence carve no false substantiation of a personal even though it might bring setback of exceeding in errors while verifying accredited personals.

This is where biometrics come into picture and becoming more and more useful and foolproof. The biological data is the sure shot way to legitimize the authentic singleness of a personal. No two human beings have carbon-copy or definite matching bundle of biological traits and each biometric trait provide divergent role for acknowledgement. There may be a few lookalikes in face patterns when it comes to some personals but definitely their heart sounds are going to be divergent.

Hence, these biometric traits play a paramount role for drawing a security schema. Practically almost all of the biometric security schemas build upon corporal vicinity of a personal, not catering to images or memories. With the upgrading of technology and IT infrastructure, biometric schemas have become the most prominent security structures. Use of Biological traits act as the base of biometrics in ever advancing technology.

Apportionment of biometric identifiers is comprehensively in two groupings:

a) Physiological – this encompasses traits like fingerprint, palm print, retina, hand geometry, face recognition etc.
b) Behavioral – this encompasses traits inclusive of gait, voice pattern, walking pattern or writing style etc.

Figure 1.1 depict above intimated subdivisions of identifiers.

Technology upgrading has also meant that identity falsification is becoming more and more easier, which in turn, has resulted that a single biometric trait may not be enough or error-free when it comes to designing a biometric schema. This thesis caters to the study and analysis of a biometric schema, groundwork of which is based on multi-modal traits, keeping in check the ease with which the required traits can be acquired and at the same time, not compromising with the end goal of having a secure biometric schema in place.

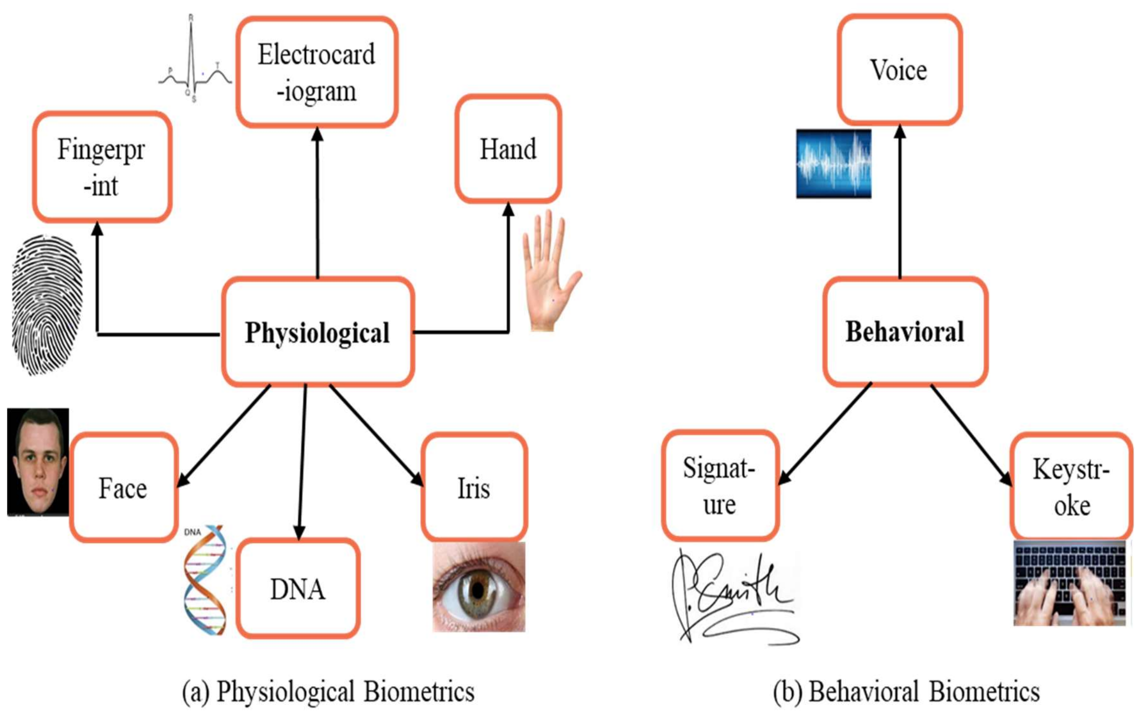


Figure 1.1 Biometric Types

1.1 BIOMETRIC SCHEMAS AND THEIR SINGULARITIES:

In technology, usage of biological traits is biometrics. For potent and effective work, these schemas depend on specific data about exclusive biological singularities. For personal identification, data is made to run through multiple algorithms in a biological schema. Several modern biometric schemas are depicted in Figure 1.2. Security applications do typically use Fingerprint and Iris scanners in day today environment.

An accustomed biometric schema, employing any biometric trait, is depicted as Figure 1.3. The multitudinal constituents of a biometric schemas are:

a) Biometric Sensor (for trait acquisition)
b) Trait extractor (select only unexampled traits)
c) Matcher (algorithm to look out for match against accumulated templates)
d) Decision (legitimate/imposter or personal labeled/not labeled)

Depending upon requirements and nature of application, a specific biometric trait is used. For example, eminently impregnable operations may not implement voice based schema, the reason of which is its susceptibility to treachery and noise but it is used for cataloging applications which implicate mobile phones.

(a) Fingerprint Scanner [5]

(b) Over air palm scanner [7]

(c) Hand Palm Scanner [8]

(d) Iris Scanner

Figure 1.2 Various biometric schemas used in day today life

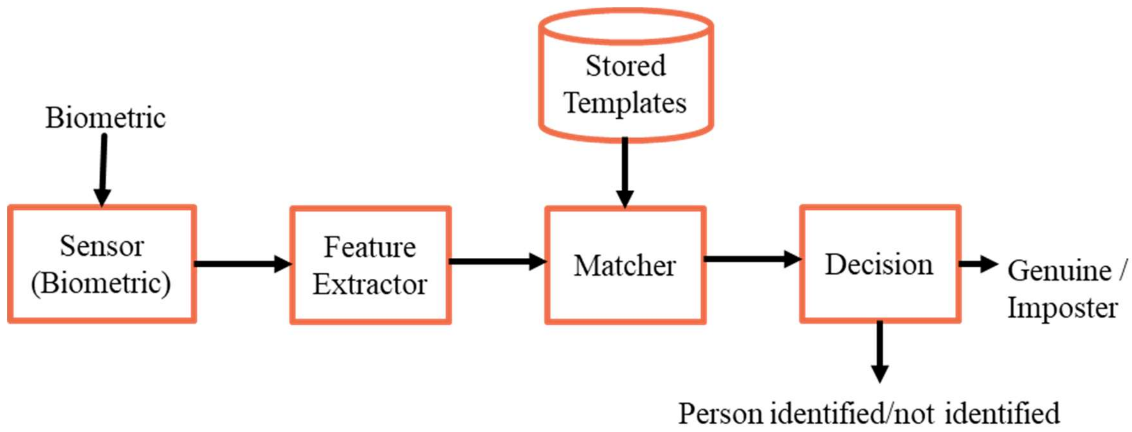


Figure 1.3 Typical Biometric system scheme

The key necessities from biometric systems are listed as below.

a) **User Friendly/Convenience:** It should be easy to use for personals, obviating any scope for hazard, salutariness or heath worry with the interface, even long-term regime side effects should also be inconsequential.

b) **Performance:** Depending on deployed surroundings, the performance of biometric schema should be as per foretold levels, which is further proportioned as equal error rate metric and metric grounded on identification error rate.

c) **Cost:** Biometric schema should be low-priced both to install and persevere, this comprehend hardware apportionment like sensor, memory, processor etc. and software apportionment like matcher, GUI etc., which rationale as direct cost whereas the investiture, training and maintenance come under indirect costs.

d) **Security:** Today with the age of wireless and internet, threats like ill-disposed incursion, spoof etc. endanger the quiescent security of a biometric schema and the origin of such endangers may be intrinsic failures or may be from foreign incursion to the schema.

Hence, security against such incursions is another front-page prospect with biometric schemas.

e) **Interoperability:** Markets have grown far and wide with voluminous vendors/brands supplying manifold hardware components for a biometric schema. What this means is a biometric schema must foothold these manifold platforms and percolate under no presupposition of same transacting circumstances. This also embodies software maneuverability including algorithms implemented within.

For singularities, the biometric schema depends on physiological and detectable traits of living beings. Not all the traits are usable and unique but there are certain paradigms which these biometric traits must effectuate and these are as below in table 1.1.

Table 1.1 Summary of Biological Feature requirements for any biometric schema

Sr. No.	Property	Brief Explanation
1	Measurable	Quantitatively measurable trait.
2	Uniqueness	Trait must be distinct for every personal.
3	Universality	The trait must be possessed by all personals.
4	Circumvention	Schema must be hack-proof when incursions happen.
5	Acceptability	Day today usage should have no issue with personal.
6	Performance	No effect of environment/operations on schema output.
7	Permanence	Time invariant Trait should be used.

1.2 FACE RECOGNITION

Face recognition is embodied into our day today life, where we come across manifold faces in our daily schedule and do hail each other as per their singleness. It is so prevailing that we don't even envision that it is a technological analogy. So, when we think on the lines that we do use Facial traits as metric to pinpoint each other, i.e., comparison grounded on these traits is done to find explicit match. In simple terms, recognizing or identifying from a video frame or digital image is face recognition.

Applications for face recognition mainly embodies security, the resultants of which are comparable to other biometric schemas like Iris and fingerprints. Self-regulating identification and deposition of any personal from the given video source or image is one of the prominent computer application of face recognition schema. For recognition, this embodies entangled computing techniques/algorithms because of conglomerate multi-dimensional structure of face. Over our lifespan, we come across manifold personals and are able in pinpointing those even if we find them after long hauls of time despite antecedents like Aging along with other divertissements like glasses, beards or hairstyle change.

Manifold efficacious algorithms are at one's disposal for exertion based on extracted facial traits and augmentations are being proposed by manifold works over these algorithms. Amelioration of computer science technologies has further boosted face recognition since nowadays, all social sites use same schema for safety, the basic gimmick of which are Facial traits are extracted, processed and comparison with stored database happens. Positive result does happen if there is match otherwise negative results are produced. A new entrant face, happening more than one time, is stored in scrutiny system for imminent references and this comprehends criminal identification.

1.2.1 Categories based on Face Recognition

Generally, there are two broader categories in face recognition.

a) **Geometrical Feature based schema:** These confide in personal facial traits which are geometric in nature like eyes, cheeks, mouth, eye brows etc. and these also embodies the geometric conjunctions between these traits. Proportionate shape, position and size of traits like eyes, cheekbones, jaw and nose are worked out based om manifold algorithms and stored. Illumination lassitude and traits intuitive understanding are the pros of these feature schemas. But due to non-reliability of measurement proficiencies and revelation of facial traits, geometric traits alone are not ample for face recognition. Hence over period of time, these proficiencies have become abandoned and limelight has altered towards appearance-based methods.

b) **Appearance based / Holistic colour based schemas / Photometric**: These are applied to either unambiguous parts or locales of face or to the unabridged face. These are statistical based schemas in which values based on images are derived and templates are compared against these values. To find a match for a new face, a KNN or Nearest neighbor can be used. The best in class proficiencies for these schemas were developed with the algorithms based on eigenface proficiency. Principal Component Analysis (PCA) was first used to truncate dimensions of the data which not only helps is catering run times but also filters our non-relevant measurements. Personals may choose to apply proficiencies like FLDA, Laplacian faces etc.

Today everyone has access to video cameras, even the mobile phones (smart phones) advancement and reach to common people has meant that digital content in form of pictures and video sequences is widespread. This has further emphasized the importance of security based on facial recognition techniques. One of the prime advantages of facial trait based proficiency is that personal need not to made stand in camera view and with movements of personals around like walking, running alone or in crowd, the schemas can extract the relevant information, even without personal aware of this. This information is very useful in surveillance and security applications.

1.2.2 Face Recognition Usage

There are three main tasks based on face recognition.

a) Authentication (verification): There are two inputs to face recognition schema – input image and identity claim. The system compares these with the claimed identity and provide yes or no as an answer, forming the basis on one to one comparison.

False Acceptance rate (FAR) depict the imposters percentage who gained access and FRR (false rejection rate) denotes the client percentage who were rejected access. Figure 1.4 depicts this application.

b) Recognition (identification): Here the personal is scrutinized against all saved templates, forming basis for one to many queries, the resultant of which is rank-wise list of appropriate matched. The max rank is deemed as the output of the schema. Figure 1.5 depicts this application.

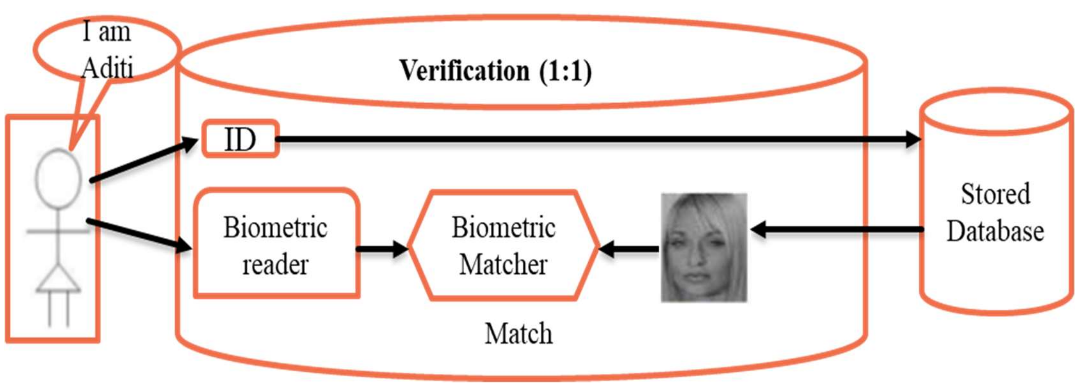


Figure 1.4 Face Verification.

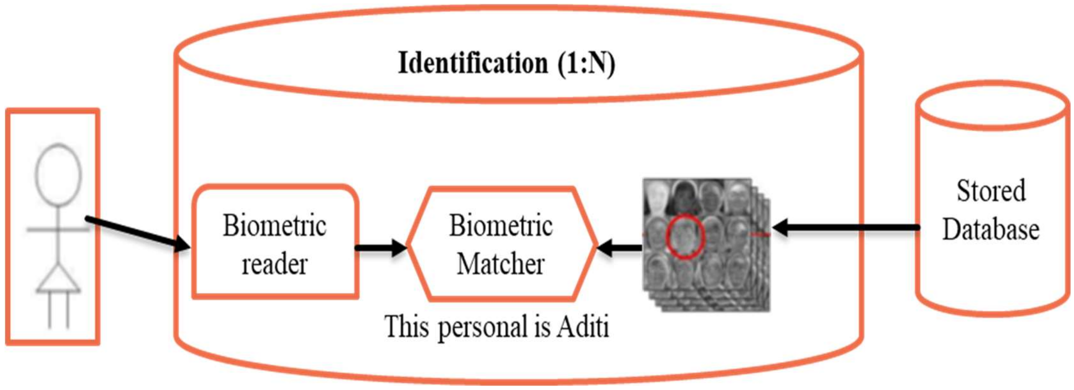


Figure 1.5 Face Identification.

1.2.3 Face Recognition process

The quest of face recognition is visual pattern recognition. With the disparities like pose, illumination etc., the 3-D human face recognition is to be done. The input data for this can be 2D single/multiple images, laser scans and 3-D cameras.

Inclusion of time dimension with still image produces a video sequence and two consecutive frames from such formed video sequence are used for identification.

There are four basic steps in face recognition systems as depicted in Figure 1.6; face localization (detection), pre-processing of face (face normalization/alignment, illumination fitting etc.), trait extraction and matching of traits.

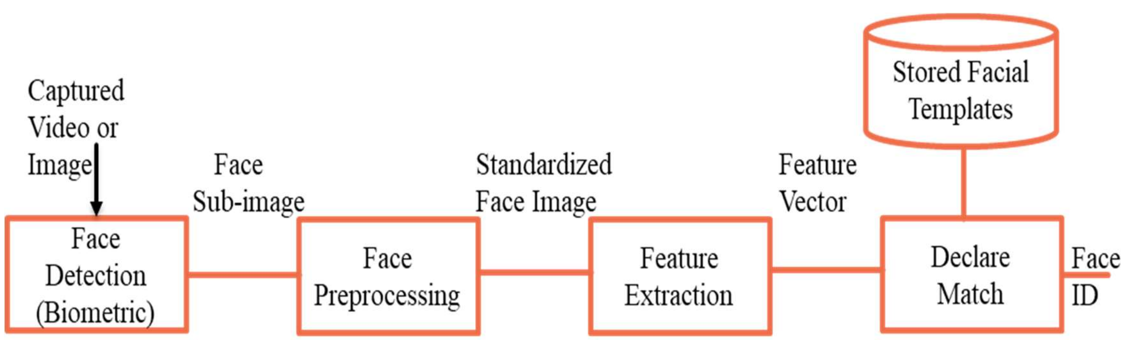


Figure 1.6 Face based biometric schema

1.2.4 Face recognition Considerations and Challenges

General considerations for face recognition are listed as below.

a) Facial expression/appearance contradistinction for disparate individuals: Facial image do depend on manifold antecedents like facial illumination, countenance and pose, camera lens angle, exposure time, lens aperture etc. which play important role in facial image and same person images are subject to large variations due to above mentioned factors. Figure 1.7 depict a twin pair, which pose another hurdle for these schemas.

Figure 1.7 Identical twin showing small interpersonal contradistinction
(Courtesy: http://www.elleuk.com)

b) Non -Linear disordered spaces which encompasses face image: Faces are a subpart of disordered manifold of image space, out of which maxima of the information is redundant in this subspace. The intension is to expunge the redundancy and noise while doing the process of image reduction and keeping the discriminative information intact, which becomes a very difficult problem considering the non-convex and non-linear manifolds of image extended by issues of translation, rotation and scaling further complicating the problem. In such scenarios, algorithms like PCA, FLDA etc. provide solution.

c) Small sample count and high/multidimensional input space Problem: Image is a high input space, for example, if we consider 16 x 32-pixel image, there is 512-dimensional space. For a personal, there are typically small image count. This small count of images for a personal may not remain plenteous for construction of an appropriate manifold.

1.2.5 Shortcomings of Face Recognition

For the sake of completeness of introduction of facial recognition systems, some cons of face recognition are listed as below.

a) With aging and over period of time, personal face exhibit contradistinctions over time, causing failures in schema.

b) Lighting changes and changes in facial countenance pose another challenge.

c) Face obstructions caused by glasses, hair, scarves etc. affect schema correctness.

This thesis is not aimed to describe the traditional Face recognition methods. We would explore about the face recognition using a single image of a person based on patch principal component analysis and merge it with the biometrics based on electroencephalograph.

First, we shall delve deep into face traits. The elected schema is quite discrepant from the diverse methodologies, most fresh endeavor of which has been in thermal image trait based, groundwork of our face trait is entropy biased identification. Further augmentation is to add DCT before performing PPCA in this schema, which not only is innovative but also assist to increase the correctness. Same would be scrutinized against the PPCA only approach, with no entropy biasing being done.

1.3 ELECTROCARDIOGRAM SIGNAL OVERVIEW

Electrical exertion of heart gauged covering skin facet is registered by applying Electrocardiogram(ECG) signal. Gauged covering the body and its facet, the heart reproduced electric potentials can be demarcated, which is taken care by medical personal by laying electrodes on body facet and demarcate the voltage being reproduced amidst them, making certain very inconsiderable current is sapped (in absolute eventuality, no current should be sapped at all as it perturbs electric potential). Over past eighty years or so, Electrocardiogram has excogitated as a paramount chunk of prevailing all-inclusive body medical intervention. A non-zero voltage or potential disparity is inspected when the medical personal allocates two electrodes on despair equipotential lines of heart electric field, resultant of which is that the locale of electrodes become a foremost here since heart electric field is locale conditional and locating electrodes pairs at despair positions of locales will provide disparate readings of voltages.

The basic question is how the electric potential is being advanced by the human heart. The ion conduction transpires inward of heart muscles and whose conduction is exposed by ECG, also called as myocardium. With every heartbeat, this change. Skeletal, smooth and striated muscles are three muscle kinds indulged in histological foundation and wall of heart. There is an electrophysiological polarization and depolarization patterning during every heartbeat, which reproduces this electric potential. ECG has transpired as an effective and useful tool to pinpoint (and detect) medical circumstances like heart attacks.

Electrode locale is graded for clinical exertion and assessment and there need to categorical electrode and lead employments as per clinical diagnostics. Below table, Table 1.2, summarizes the manifold electrode positions, which can be used to demarcate electric potential and hence as act as biometric trait for personals.

Table 1.2 Electrodes and their positions

Label of Electrode	**Placement of Electrode**
LA	Placed on Left Arm. Avoid Thick Muscle.
RA	Placed on Right Arm at same location as LA.
LL	Placed on left Leg. Lateral Calf muscle.
RL	Placed on right leg at same location as LL.
V1	Placed on just right of breastbone(sternum) in fourth intercostal space (space in between rib 5 and rib 4)
V2	Placed on just left of breastbone(sternum) in fourth intercostal space (space in between rib 5 and rib 4)
V3	Placed between lead V4 and V2.
V4	Placed in mid-clavicular line in between rib 5 and rib 6 (fifth intercostal space)
V5	Placed in left anterior auxiliary line, horizontal with V4.
V6	Placed in mid-auxiliary line, horizontal with V5 and V4.

There is difference in terms “lead” and “electrode”. An electric circuit is devised with electrocardiograph when the personal body meets conductive pad, and this conductive pad is depicted as electrode. The electrode connector is depicted as lead. Hence, there is subtle dissimilarity amidst these two terms. Ten electrodes are used in twelve-lead standard Electrocardiography. Nowadays, with technology fast growing, the number of electrodes have declined through manifold works.

Electrocardiogram is a singular trait for every personal, where most importantly, the liveliness of the personal is reassured when we apply electrocardiogram as a trait vector for credential establishments. The challenge becomes more complex since even with each personal, the electrocardiogram wave shape varies as per his/her emotional, physiological, and physical conditions and even the external environment proves to be antecedent to these variations.

Electrocardiogram signal is comprised of below major components.

a) P Wave
b) QRS Wave
c) R wave
d) T Wave

Table 1.3 summarizes the brief description and key properties relates to the above-mentioned electrocardiogram signal components. Same is depicted in Figure 1.8.

Table1.3 Key Ingrained of different waves and segments.

Type of Wave and Segment	**Source of wave /Origin**	**Amplitude (in mV)**	**Duration (in seconds)**
P	Upper heart compartments (atria)	0.25	--
Q	Lower heart compartments (ventricles)	¼ of R	--
R		1.6	--
			--
T	Electrical bootstrap of lower heart compartments	0.50	--
PR	--	--	.12 - 0.2
QRS	--	--	< 0.11
ST	--	--	0.05 - 0.14
QT	--	--	0.34 - 0.44

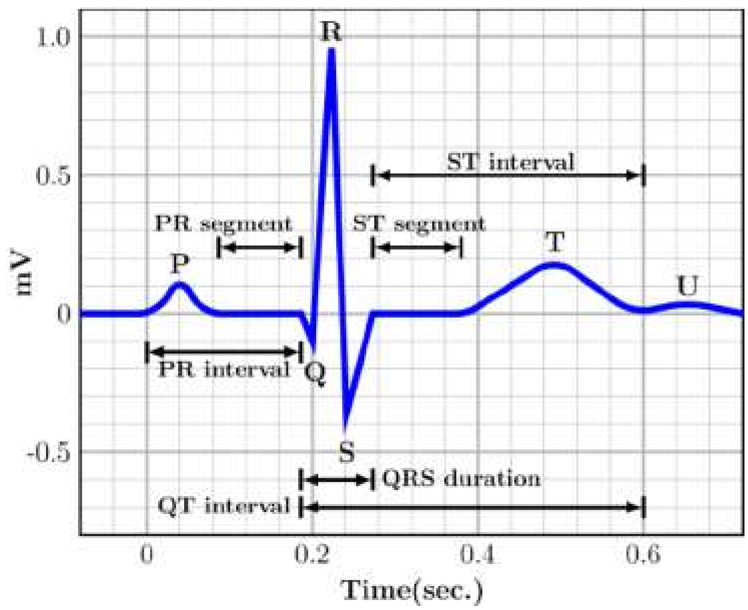


Figure 1.8 Pictorial Depiction of Electrocardiogram waves and various segments.

The personal identification is based on above-mentioned waves and segments, which these wave parts form. The association and co-relation across these waves and their segments form a distinguished trait vector for a personal. These vectors are reserved in a repository called the database and used for compared for identification and authentication.

1.3.1 Feature types for Electrocardiogram

There are two propositions to the virtue types for electrocardiogram based biometric apparatus. One of these is fiducial established and other is non-fiducial established perspective.

As stated earlier, there are evident and obvious points in an electrocardiogram waveform and the usage of these evident points form basis of fiducial dependent establishment. This approach hinge on the confined (or local) properties of the electrocardiogram and alliance between the points like amplitude difference, time unit locations (temporal) etc. Biometric templates are formed based on these confined peculiar traits in fiducial dependent advent.

The peculiar points distinguishing the electrocardiogram miss the overall particulars which may convey some distinct information. The statistical information projected by the full cycle of electrocardiogram signal is utilized in non-fiducial based propositions. Manifold algorithms are advocated over the decade like discrete Transform (DCT), linear discriminant analysis etc. This type of technique does capture unessential information and always require removal of unneeded or dispensable features based on the norm to maximize the inter-personal variability and reduce the intra-personal variation as low as possible.

1.4 PREVIOUS WORK

In [4], Sellami Abdelkader unturned the idea of handling the electrocardiogram based biometric structure by exploiting the use of bounded (local) traits (i.e., fiducial traits) and a correlation score based decision operation results identification. The major infirmity of this schema is temporal changeability is not dealt here.

In [2], Samik Chakraborty, *et al*. prospected the convention of integration of face and electrocardiogram virtues. The ideology exploits the portrayal of frontal face in from of a texture signal. Also, the electrocardiogram R peaks in terms of time and amplitude are passed-down to the identification schema. The circumspection of this disposition is the components which include alignment issues of face, anomalous heart condition, age diversity etc. resulting in error prone identification.

In [3], MD Saiful Islam, provided an excellent insight in multiple templates possible when we investigate the heart signal. His work is targeted to uncover the best combination of various fiducial or non-fiducial traits that a personal must work with electrocardiogram signal. While working with other modalities or a union of unalike modalities, this approach can be used and better identification rates can be hit.

In [20], S. A. Israel, *et. al*. examined the schema for exploiting face and electrocardiogram as source of biometric traits and comparison of the results based on individual traits and then union of the two traits is done. This is one of the first works in combining these two modalities. The results obtained with both combined are much better than any single of these. The shortcomings of this schema were to explore impacts of multiple angles, poses in face trait and issues coming due to anomalous heart condition.

Paper [9] canvasses a method to identify and verify personals based on Face virtues. The specialty of this schema is that there is only one image available for the system to learn. The schema uses the accustomed algorithms of principal component analysis in single dimension and two-dimensional scenarios. The principle works out better results than its predecessors but the faultlessness of the schema needs lot of modifications and work.

In [1], Basma Ammour, *et. al.* canvassed a method based on two biometric characteristics or features. The traits chosen in this schema are Iris and Face. The work is extended to the exploitation of various fusion methodologies for final decision making. Further, multiple databases are delved into for final results compilation. The proposal emphasizes the use of multiple biometric virtues for the personal verification. Other virtues can also be explored and combined in similar fashion to develop other schema which may provide more authentic, precise and robust results.

1.5 THESIS STRUCTURE, GOAL AND ORIGINAL CONTRIBUTION

The work put in this thesis is to establish a biometric schema based on two unrelated biometric traits for exceeding the efficiency and correctness of identification system. Biometric traits examined in the proposed schema are electrocardiogram and face traits.

First, we shall delve deep into face traits. The elected schema is quite discrepant from the diverse methodologies, most fresh endeavor of which has been in thermal image trait based, groundwork of our face trait is entropy biased identification. Further augmentation is to add DCT before performing PPCA in this schema, which not only is innovative but also assist to increase the correctness. Same would be scrutinized against the PPCA only approach, with no entropy biasing being done.

The second trait being worked is Electrocardiogram. The trivial alterations are achieved in prior filtering dispositions for electrocardiogram signal. Once we have filtered electrocardiogram signal at our use, we would oblige to find out the unmistakable characteristics of this trait, which are generally called as feature set. Electrocardiogram signal has these numerous unmistakable traits, out of which, we have selected the fiducial points and temporal locale of these points to design a biometric schema. As it was analyzed later by us that these fiducial information is not sufficing to achieve a satisfactory accuracy, we added the full PQRST part of the beat to our Electrocardiogram trait set. This addition has shown tremendous enrichment to our accuracy results, strengthening our methodology.

There are certain physiological movements and there may be circumstances of pathological happenings, the resultant of which is modification in the Electrocardiogram signal, which further will hamper the accuracy of any schema that is designed on any trait extracted from the Electrocardiogram signal. Situations like coming back from a run or heavy breathing also produce modifications in Electrocardiogram signal. On the same tone, the traits based on face vary with expression, appearance, surroundings, light settings, illumination etc., making these traits susceptible to wrong results. Hence, none of these single traits based schemas become successful in identification purposes, result of which is the search for some schema, where the shortcomings of one trait are overcomes by other trait in any way.

This has led to inquest for the multimodal biometric schemas, where more than one trait is being worked with. We have scrutinized the face and Electrocardiogram merged traits based schema, which has further made way for innovative and easily put to use fusion schema. The novel fusion schema worked for these two biometric traits does not put any bias on any the traits but works to add the end outputs of the two separate schemas, such as they are employed independently, the best of which is selected as end identification of personal.

The results do echo the proposed schema to boost accuracy.

CHAPTER 2

FACE BASED BIOMETRIC SCHEMA

We have built on the work done by Mr. Kanan[14] for face based traits extraction. These are further used to merge with Electrocardiogram traits to work out a much accurate biometric schema. Most of the work has been done with PCA, when working with face traits, either it may be one dimensional version or two-dimensional implementation of PCA.

Basic face based identification system is depicted in Figure 1.6 earlier in chapter 1. The steps that are implied in this are same as general biometric, involving acquiring face based unique traits, accumulate them for all personals to be entered in system and then perform the task of classifying (identification task) these.

The data space which is used as an input to PCA algorithm, is a highly correlated among themselves, which is linearly transformed to a new space, where the data sets are now uncorrelated. This new space of projection is known as eigen space and it has been popular schema while working with face traits. This also minimize the dimensionality of the feature space to a large extent, which is totally dependent on the number of eigen vectors we choose to work with, which in turn can be selected based on magnitude of eigen values.

Figure 2.1 depicts the schema we have proposed in our analysis with face traits. We shall dwell deep into each of the proposed schema in next sections.

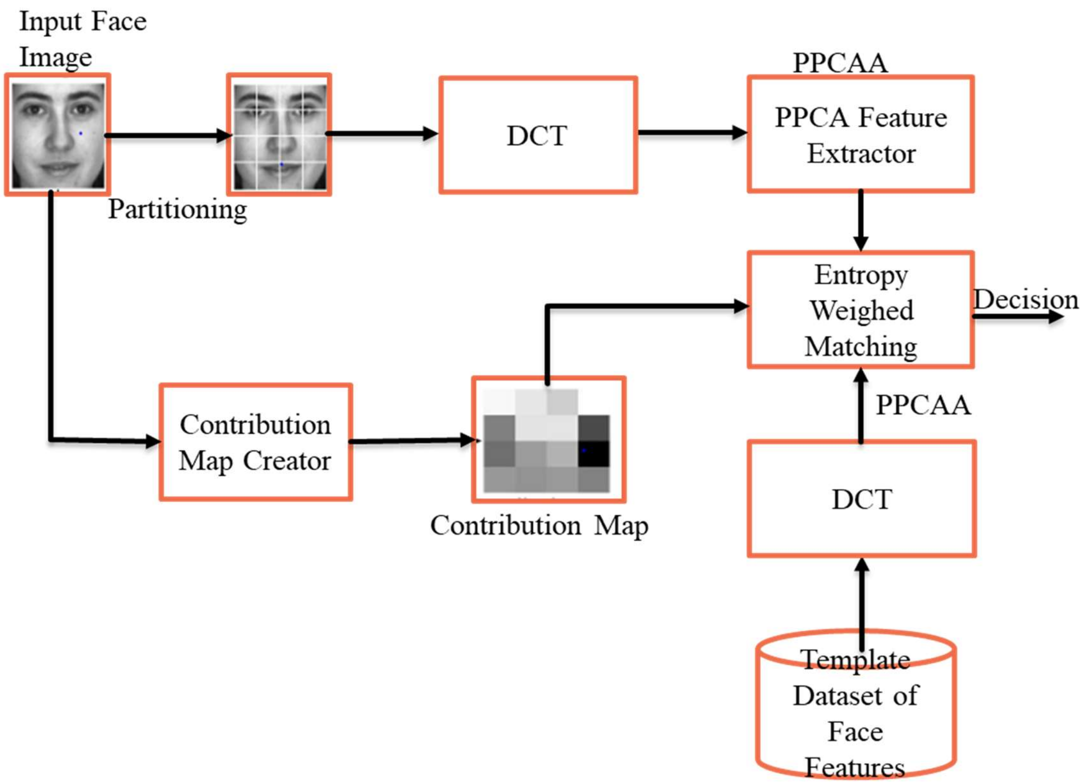


Figure 2.1 Proposed schema for face based biometric

2.1 PATCH PRINCIPAL COMPONENT ANALYSIS METHODOLOGY (PPCA)

Steps engaged in this approach are as below.

a) Image is disjoined into several distinct small chunks called patches. These patches are done in such a way that one patch does not overlap with any other and are of same size. Let g(x,y) is face image of aspect ratio NxN. Chunk size is defined as LxL. Hence, number of chunks can be calculated as $(N/L)^2$. Equation (2.1) depict the patch as below

$$g_{p,q}(a,b) = g(L(p-1)+a, L(q-1)+b) \qquad (2.1)$$

where chuck at position (p,q) = $g_{p,q}(a,b)$, $1 \leq$ a,b $\leq$ L and $1 \leq$ p,q $\leq N/L$

These small images can be listed as L^2 size vector.

We shall find mean of small chunk at (p,q) among all learning image sate as per Equation (2.2).

$$g_{p,q}^{mean}(a,b) = \frac{1}{M}\sum_{i=1}^{M} g_{p,q}^{i}(a,b) \qquad (2.2)$$

where $g_{p,q}^{i}(a,b)$ is small chunk located at (p,q) in i^{th} face image.

b) Perform DCT over individual chunk.

Now we shall apply PCA over all these small chunks individually.

c) Normalization Step: This is performed as per Equation (2.3).

$$B_{p,q}^{i}(a,b) = g_{p,q}^{i}(a,b) - g_{p,q}^{mean}(a,b) \qquad (2.3)$$

where 1 ≤ i ≤ M and 1 ≤ p,q ≤ $N/_L$.

d) Covariance Matrix: At location(p,q), it is calculated as per Equation (2.4).

$$C_{p,q} = \frac{1}{M}\sum_{i=1}^{M} B_{p,q}^{i}(a,b) \; . B_{p,q}^{i^T}(a,b) \qquad (2.4)$$

e) Find L' most significant eigen vector and chunk $g_{p.q}(a,b)$ is projected as per Equation (2.5).

$$PPCA\left(g_{p,q}(a,b)\right) = L_{p,q}^{T}\left(g_{p,q}(a,b) - g_{p,q}^{mean}(a,b)\right) \qquad (2.5)$$

f) Final Face image representation is done by using individual PPCA of each of the small chunks and concatenating them as a single vector (Equation 2.6).

$$PPCAA[g(x,y)] = \left\{PPCA\left(g_{p,q}(a,b)\right) \mid 1 \le p,q \le N/_L\right\} \; (2.6)$$

2.2 CONTRIBUTION MAP (CM)

We have been well versed with calculating the entropy of any system, with same concepts entropy related to an image is calculated. The same can be achieved using Equation (2.7) as listed below.

$$H[g(x,y)] = -\sum_{j=1}^{n} p_j \log(p_j) \qquad (2.7)$$

The terms n and p_j depict the resolution and probability corresponding to j^{th} gray level.

We also need to consider the importance of entropy calculation. The information encompassed in specific part of image is captured quantitatively by this analysis, which further put strong case for local traits in a small chunk (which is part of full image in this case and trait becomes intensity variation).

Mathematically, this may seem to be a cumbersome process that we will need to look into local region entropy but by using a windowing method, where window keep on shifting its location, we can use Equation (2.7) to generate the whole image entropy map (EM). For every pixel, use Equation (2.8) as depicted below for entropy calculation. MW represents the moving window.

$$EM(i,j) = H(G(i,j)_{MW}) \qquad (2.8)$$

where $G(i,j)_{MW} = \left\{g(x,y) | x \in \left[i - \frac{MW}{2}, i + \frac{MW}{2} - 1\right], y \in [j - \frac{MW}{2}, j + \frac{MW}{2} - 1]\right\}$ (2..9)

We shall average the EM in the already defined small chunk since this small chunk is represented by a single PPCA value.

For a chunk, the net Contribution Map (CM) can easily be find out using the below formulae in Equation (2.10).

$$CM_{p,q}(a,b) = \frac{1}{L^2}\sum_{x=1}^{L}\sum_{y=1}^{L} EM(L(p-1)+x, L(q-1)+y) \quad (2.10)$$

where, $1 \leq p, q \leq {}^{N}/_{L}$

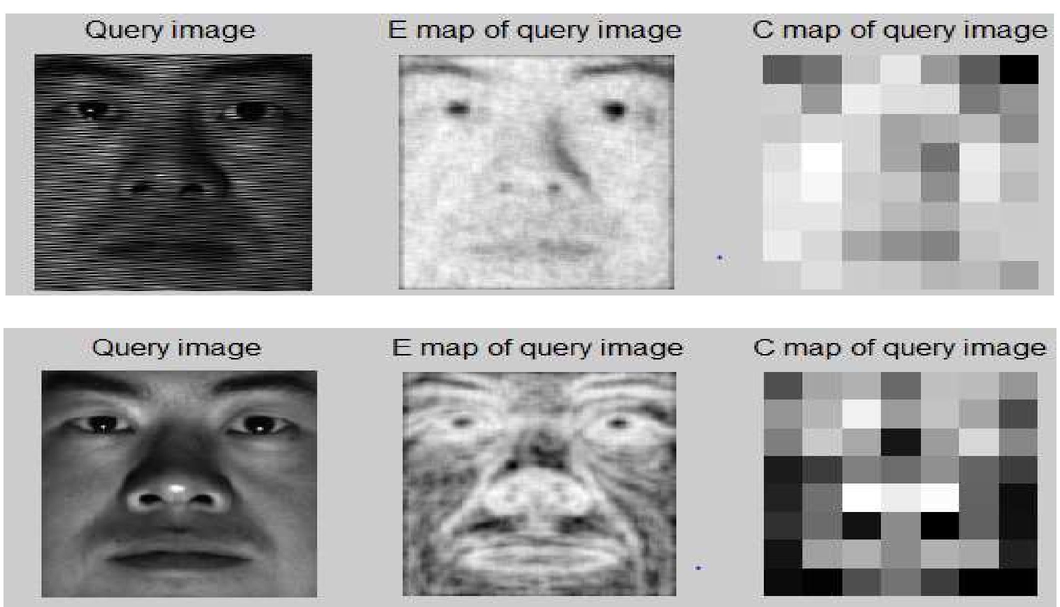
Now we do have all the inputs that we need to have for identification of a personal and these are then utilized for biometric schema formation.

This CM is not a constant value as must be evident by the fact that it is driven by the entropy in local portions. Hence, using this in a weighted scheme has proven to be much useful. Further, we tried to work out the best selection for bifurcating the image into small portions called chunks or patches and it is totally an iterative process where we started with first dividing into two parts and the going on based on the results we obtained were up to the mark or now. Finally, the numbers that worked out the best accuracy is any value between five and eight. All our results are being published with value eight here.

Figure 2.2 depict the CM plots with change in illumination. Two things are evident from these plots and these are as below.

Higher Intensity => More gross in CM and vice-versa.

Higher weight is associated with most important traits like nose, mouth and eyes.



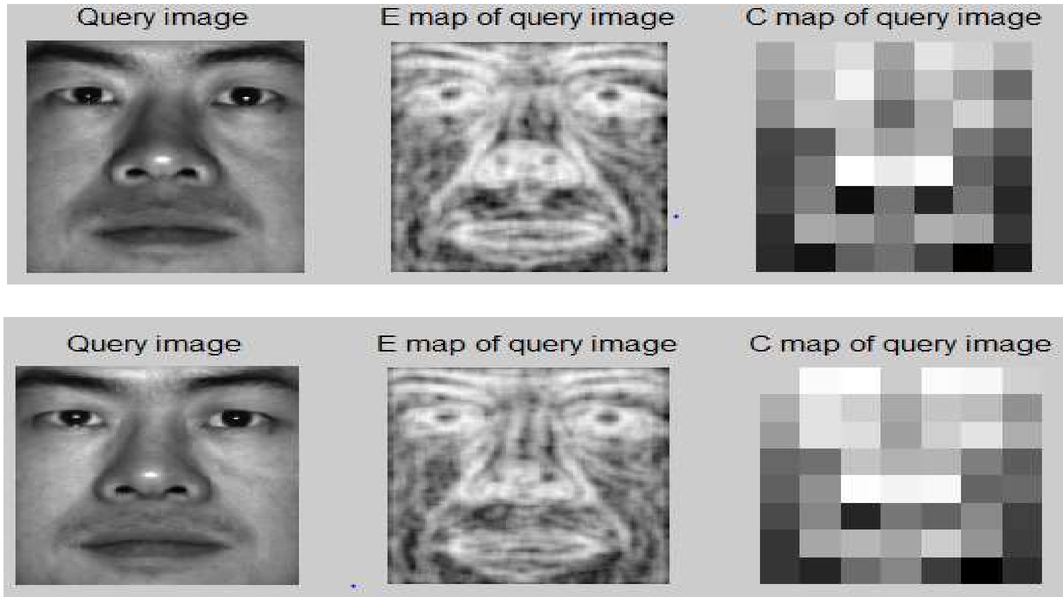


Figure 2.2 CM Variation of Face image with illumination

2.3 CLASSIFICATION

The final objective of a recognition/identification task is to classify amidst available classes or personals.

Here we have face traits saved a PPCAA. Every PPCAA, used to record face trait, has a concorded CM. The basic thought here is to find out the CM grossed distance metric among saved vector of a subject and the questioning vector. Hadamard metric is used for pronouncing distance. Equation (2.11) depict this as

$$D(g(m,n), l(m,n) = \left\| \overline{EW\left(PPCAA\big(g(m,n)\big)\right)} \circ \left(\overline{PPCAA\big(g(m,n)\big)}\right) - \overline{PPCAA\big(l(m,n)\big)}) \right\| \qquad (2.11)$$

The results are listed in the final section of this thesis.

CHAPTER 3

ELECTROCARDIOGRAM SIGNAL BASED BIOMETRIC SCHEMA

Every personal has distinct electrocardiogram signal. This signal has specific advantages like ensuring that the personal is lively (and not an image or stored template), making it a robust tool to design a biometric trait based system. The analysis and results certain that the Electrocardiogram (ECG) has indeed a high identification accuracy in proposed schema.

The direct use of electrocardiogram signal acquired from a personal is not beneficial in biometric systems as there are several potential noise sources impacting this signal behavior and temporal distributions. The noise accompanying the Electrocardiogram [ECG] signal may be resultant of internal factors (inside body) or external influences or both internal and exterior influences. So before going into the nitty-gritty of the schema, we need to look into the diverse influential factors and methods to remove these potential interferences.

3.1 ELECTROCARDIOGRAM ARTIFACTS

Below sections describes the multiple electrocardiogram artifacts.

a) **Power Line Interference (PLI):** The frequency associated with power supply is 50-60Hz. This interferes with the original Electrocardiogram signal and distorts it. The base frequency (50/60Hz) as well as its multiples (harmonics) may yield frequency spectrum spikes and deviate the Electrocardiogram signal (ECG).

   The dominant originators of PLI are:

   - Power line electromagnetic intervention.
   - Cables associated with Electrocardiogram apparatus may have stray current.
   - Unapt Grounding.

Adaptive technique based filtering is very effective to cater PLI. Figure 3.1 depicts the PLI behavior.

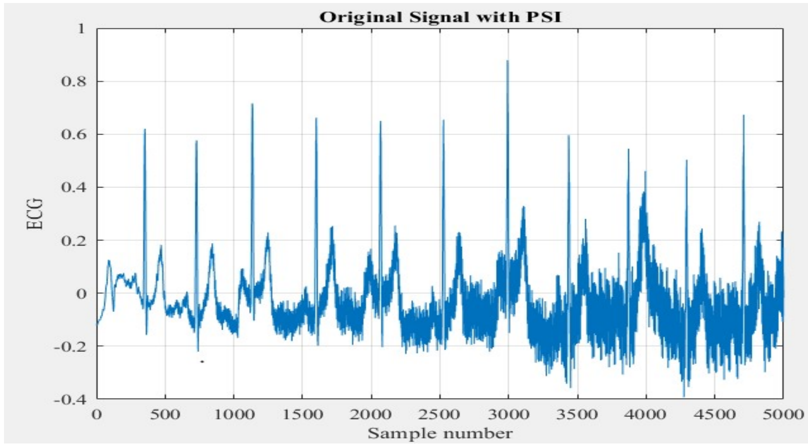


Figure 3.1 Interference resultant of power line

b) **Motion Artifacts:** While capturing the Electrocardiogram signal (ECG), the personal may have brisk (or hurried) chest movements or coughing etc. which can make the potential of Electrocardiogram signal undergo immediate change. Measures such as adaptive thresholding help cater these artifacts. Figure 3.2 represent the Electrocardiogram signal intermixed with motion artifacts.

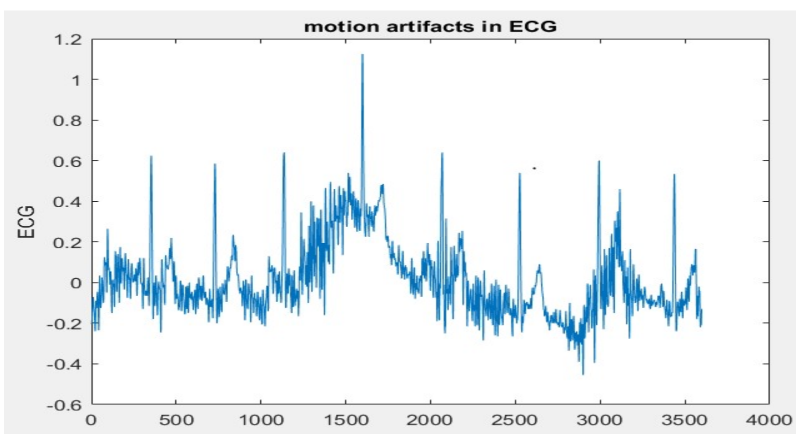


Figure 3.2 Motion Artifact

c) **Baseline Wander:** Base line drift is another caption for baseline wander (BW) artifacts. The spectrum occupied or affected by these is majorly the low frequency components, typically the range up to 0.5Hz. A personal, who is undergoing the Electrocardiogram analysis, may observe the deviation in electrode location, which may be resultant of coughing, body displacement or breathing. This changes the baseline which was earlier at zero potential especially affecting the ST segment. The behavior of Baseline wander (BW) is expressed in Figure 3.3. High Pass filters, which make designed to make sure to preserve the lowest Electrocardiogram signal frequency components, are very useful in removal of base line drift artifact.

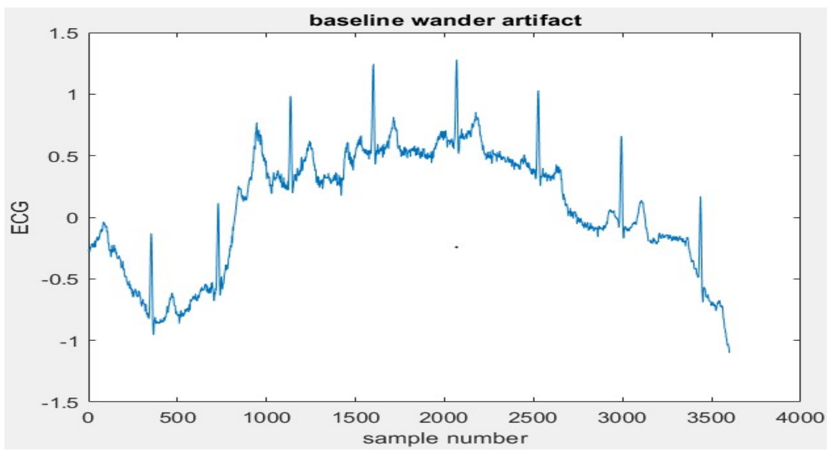


Figure 3.3 Baseline Drift

d) **Muscle Contractions:** Electrocardiogram apparatus has multiple electrodes coming in contact of body and these underlying body muscles do yield some electric potential. This artifact is not limited to a specific frequency band but extend along the full PQRST segment, which makes it much challenging and problematic to filter and remove this noise. The physiological states of a personal like exercise do also add to this kind of noise. The limited low frequency Gaussian noise with short-lived bursts can be used to model this noise merging and distorting Electrocardiogram signal.

e) **Electrosurgical and Contact Noise:** There may be the case that the body contact electrodes may get loose and the connection or body touch to record the electric activity is removed. It may be temporarily or long-lasting disconnection. Electrocardiogram apparatus include cables, amplifiers, probe electrodes etc. which are source of electrosurgical impact. Figure 3.4 depict this interference.

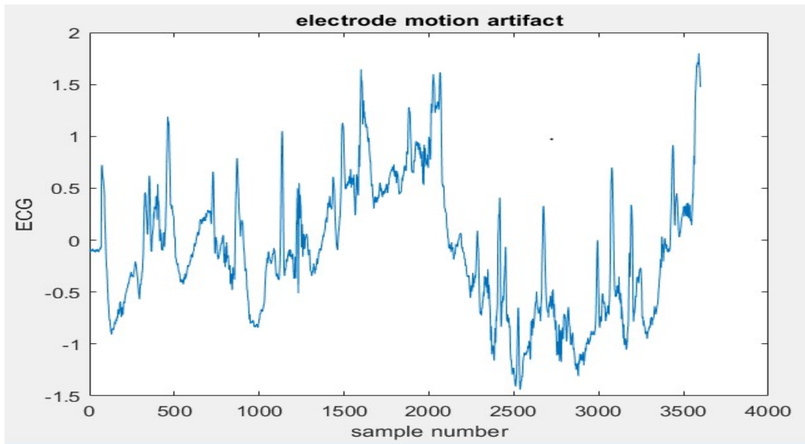


Figure 3.4 Noise due to Electrode Motion

3.2 PRE-PROCESSING OF ELECTROCARDIOGRAM SIGNAL

Electrocardiogram signals need to be pre-processed in order to use it for extraction of biometric traits. Above mentioned noise sources (section 3.1) need to be exuded from the original acquired Electrocardiogram signal. Several diverse schemas are put forward by multiple authors for extracting a clean Electrocardiogram signal, which is devoid of interferences mentioned earlier. We would be going over major filtering steps and then in the end would propose the best combination that we have used in our work.

As the first step, we need to know the frequency components of Electrocardiogram signal. For exploiting numerous filtering techniques, let us look at Electrocardiogram signal and its depiction in frequency domain.

Let the pure Electrocardiogram signal is s(t) and the noise or the interference affecting the signal is n(t). Hence the observation becomes

$$z(t) = s(t) + n(t) \tag{3.1}$$

Now the pre-processing objective is to retrieve the pure Electrocardiogram signal s(t) from z(t). To do this, we would use filtration whose selection needs the frequency domain knowledge of the signal. This frequency domain proficiency is acquired using the Fourier Transform. It can be extracted using the below formulae.

$$Z(f) = \int z(t)e^{-2\pi ft}dt \tag{3.2}$$

$$z(t) = \int Z(f)e^{2\pi f}\ df \tag{3.3}$$

There is another seasoned version of the Fourier Transform labeled as Short-time Fourier transform (STFT) (Equation 3.4) which has key tracts as listed below.

1. Signal is dissected into multiple windows resulting and Fourier Transform is exploited with each windowed resultant.
2. Both frequency and time information is available at same time in this.

$$STFT_t^f(\tau, f) = \int [z(t).w(t-\tau)]e^{-i2\pi f}\ dt \tag{3.4}$$

To explore the overall frequency spectrum, Electrocardiogram signal is dissected into numerous time sub-parts (also referred as sub-bands), which enable the user to consider the frequency details at various temporal instances.

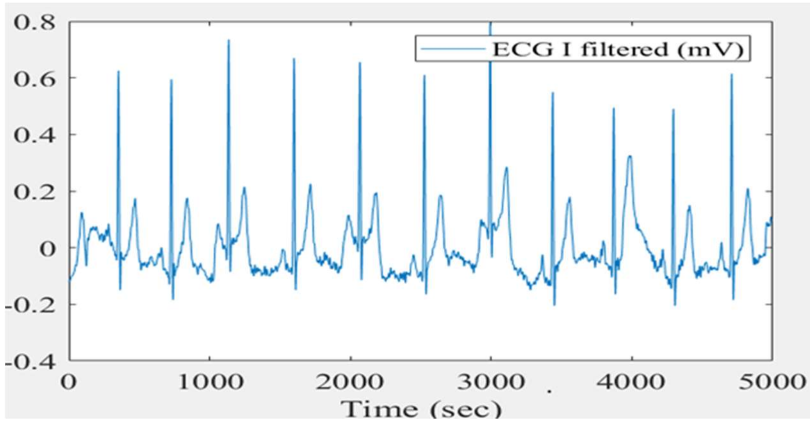


Figure 3.5 Electrocardiogram Signal (in Time Domain)

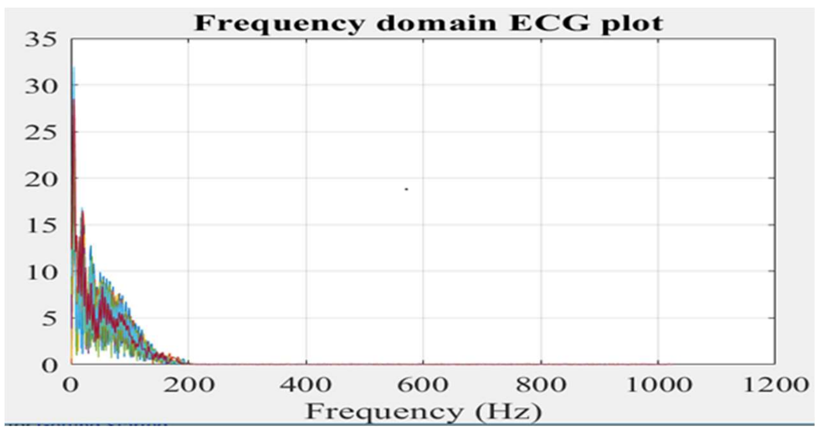


Figure 3.6 Frequency Spectrum of Electrocardiogram Signal

Above Figure 3.5 depicts the Electrocardiogram signal in temporal domain and the frequency details of same signal are captured into Figure 3.6. The main find which is obvious from the frequency domain plot is that the majority or almost all the Electrocardiogram signal is concentrated in the spread of 0.5-200 Hz, with all maxima in 0.5-100 Hz. This is important piece of information for us while going to remove the noise embedded by variety of sources.

Now let us go over details of some of the filters explored by us to get the pure Electrocardiogram signal.

3.2.1 Wavelet Transform Filtering

By nature, Electrocardiogram signal is a non-stationary signal which shows transient and time-varying behavior. With STFT, we have the pre-defined (or user defined) fixed window, which makes the analysis very cumbersome with these non-stationary signals. To remove this hindrance, wavelets were proposed. Wavelets have waveforms with peculiar characteristics such as zero average, generally non-symmetrical and limited duration.

The window duration will vary depending upon which frequency components we would like to extract. This relationship is listed as below.

Frequency Component = High => Small size window

Frequency Component = Low => Long Window

Now these variable length windows covering different temporal instances of a signal is achieved by shift and stretch of a basis function termed as mother wavelet. Continuous-wavelet Transform (CWT) can be analyzed using Equation (3.5).

$$\omega(a,\beta) = \frac{1}{\sqrt{a}}\int s(t)\omega\left(\frac{t-\beta}{a}\right)dt \qquad --(5)$$

where a is accountable for scaling and shift of mother wavelet is achieved using β. Table 3.1 depict this behavior.

Table 3.1 Characteristics of Wavelet transform with Frequency zone

Sr No.	Frequency Zone	Frequency Resolution	Time Resolution
1	High frequencies	Poor	Good
2	Low frequencies	Good	Poor

There is an increased popularity for Discrete Wavelet Transform (DWT) as compared to its continuous counterpart. This is because of the reason that it is easy to work with some discrete shifts and scales, which in this case, is in the power of 2. There is no degradation of accuracy in DWT case. If we take the case of an image and apply 2D-DWT on it, then image is segregated into four sub-parts, also referred as sub-bands. Now the straightforward way to generate DWT analysis is through utilizing filter banks, forming a stack to the level of coefficients user wants to extract and which constitute of Low pass (LPF) and High pass (HPF) filters. Figure 3.7 depicts the extraction of DWT coefficients at numerous levels via usage of LPF and HPF banks.

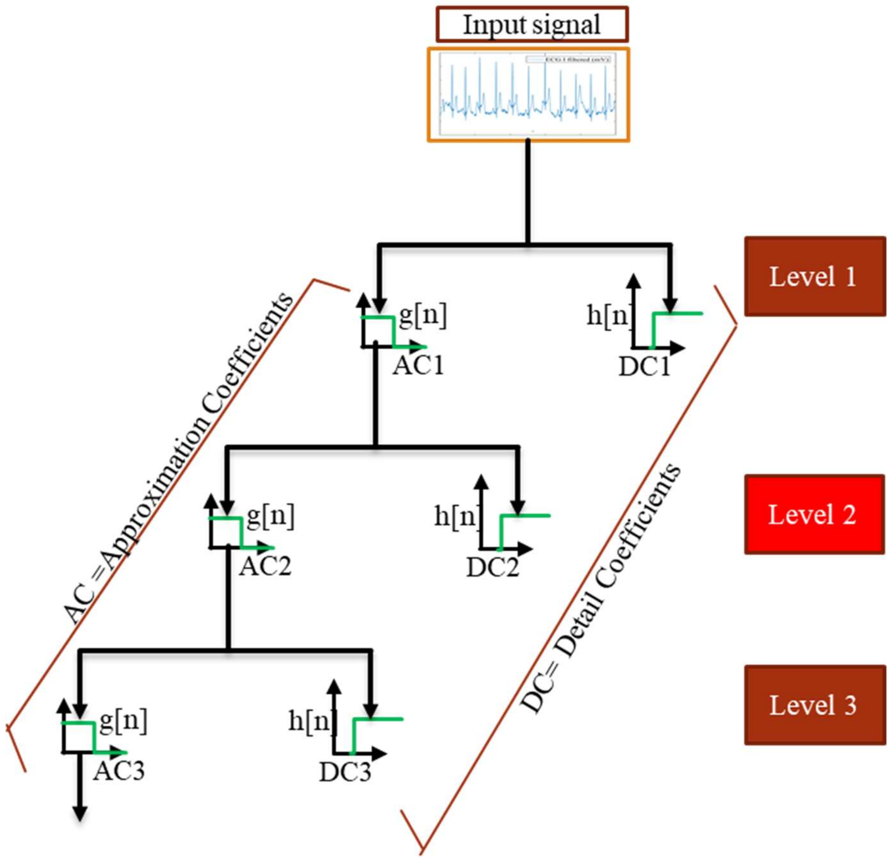


Figure 3.7 DWT in terms of Filter banks.

To explore the details of the frequency divisions at each level of DWT, we could see this in case of Electrocardiogram signal as explained here. As in equation 1, z(t) is signal captured from a personal which may have added numerous noise. z(t) has a range of 0-500Hz. Ranges of frequency up to four levels is listed as:

AC1 = 0-250 Hz ; DC1 = 250-500 Hz => DC1 is noise (High Frequency)

AC2 = 0-125 Hz ; DC2 = 125-250 Hz => DC2 is again mostly noise part.

AC3 = 0-62.5 Hz ; DC3 = 62.5-125 Hz => AC3 reflects PSI

AC4 = 0-31.25 Hz ; DC4 = 32.25-62.5 Hz

To work with numerous variety of signals, either manmade or natural, there are several wavelets available such as Daubechies, orthogonal, Symlet, Haar etc. Since the shapes of numerous signals can be complex like multi-order polynomials, so wavelets prove to be much better for signal denoising. DWT is usually followed by thresholding which again holds multiple ways to do it. DWT has its own plus points over FFT (Fast Fourier Transform). Only functions in play in FFT are cosine and sin and their powers whereas different dilations and shift options prove wavelet as a powerful tool. Moreover, the concurrent frequency and time resolution is always the basis of wavelets and DWT.

3.2.1.1 Use of Wavelet Filtering for baseline Wander Removal:

As per the insights of behavior of wavelets at various levels of DWT and knowledge of baseline drift (refer 3.1 section), we see the interference is happening at low frequency zones and we work with db8 wavelet in our setup. Our approach is listed as below.

a) Choose db8 wavelet and decomposition at level N=9 for DWT.
b) Approximation Coefficients (AC9) are used to regenerate the original input signal.
c) Baseline Corrected Signal = Original Input Signal – AC9

Same is reflected in Figure 3.8 and 3.9.

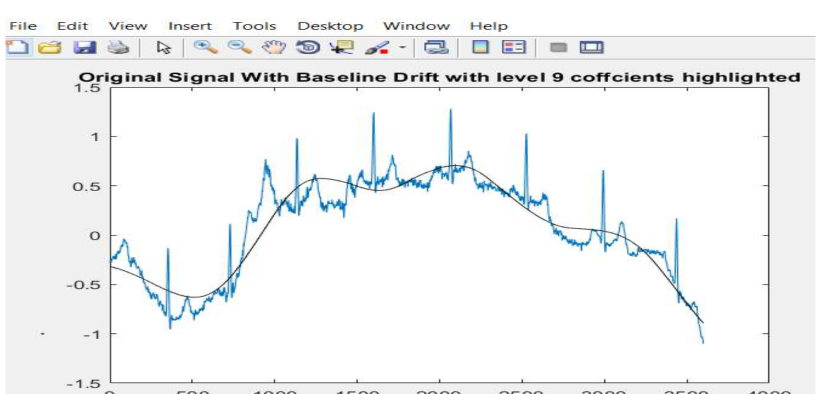


Figure 3.8 Original ECG signal with Level 9 db8 wavelet approximation coefficients

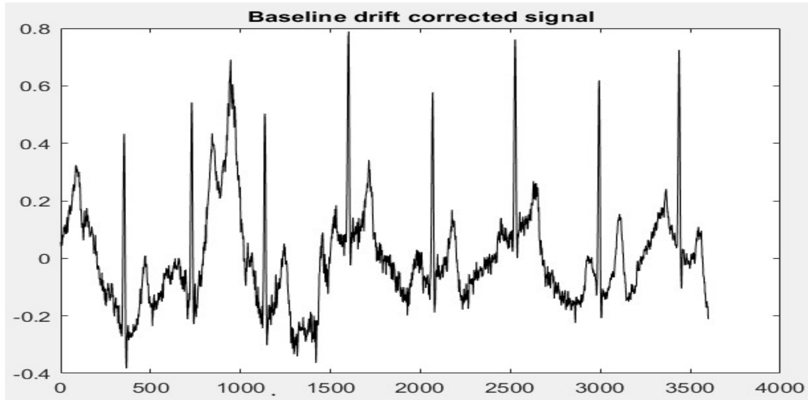


Figure 3.9 ECG Signal devoid of Baseline Drift

3.2.2 Adaptive Filtering

Noise coming from Power supply is in the range of 60 Hz and its multiples, also referred as harmonics. Also, the behavior of noise is varying and random, hence we need the filter behavior to adapt to the input to be effective and efficient. Linear filters don't satisfy this criterion as they have a rigid transfer function. It has resulted in advancement in field of adaptive filters.

Some measurement vector or matrix must be associated while looking for the tweaking of the transfer function of an adaptive filter. The prominence in conversed schema is the mean square extent of the error amidst the two values, one of which is the measured signal from the filter output and other is the input reference signal. This value is re-iteratively checked by the internal design or algorithm of the filter and it is deemed to be less than some personal defined value. Hence the weights or values associated with the filter change as the process of the reducing the matrix or measure function to some pre-defined value. This has resulted in the term 'adaptive' for the filter and basis of all the work that goes behind the design of such methods.

This type of response is very beneficial while working with PSI in Electrocardiogram signals. The mixing of power supply variant caused noise results in high frequency artifacts getting mixed with Electrocardiogram signal, specially the signal part which corresponds to low frequencies. The 'adaptive' nature is implemented using the feedback loop as depicted in figure 3.10 below.

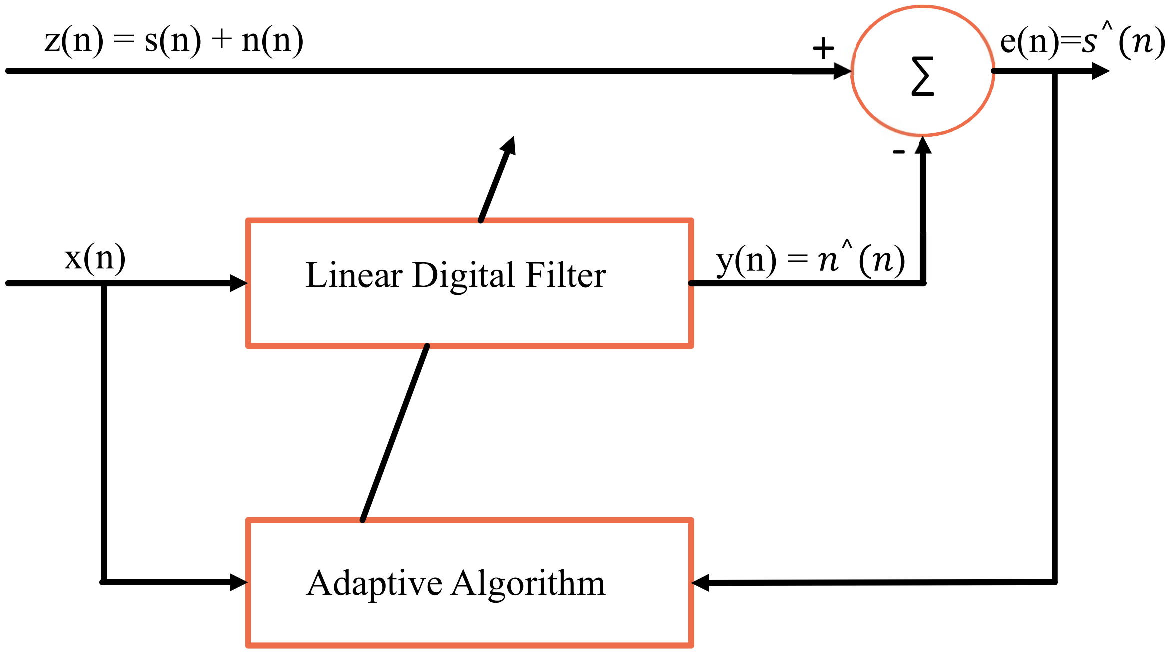


Figure 3.10 Adaptive Filter Block Diagram

3.2.2.1 Our Approach for Adaptive Filters for removal of PSI

Adaptive Filter is designed with the below settings.

a) Ws = 50 Hz.

b) dA = 1.4

Figure 3.11 refers to Electrocardiogram signal with PSI. Filter designed has a response as depicted in figure 3.12. The clean signal, i.e., signal devoid of PSI is represented in Figure 3.13.

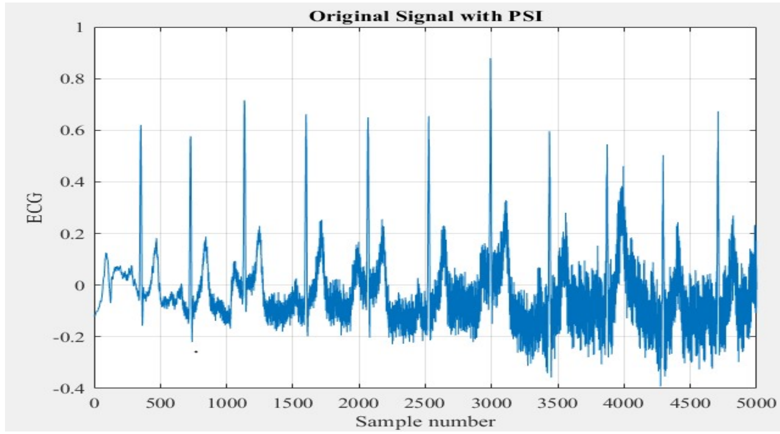


Figure 3.11 ECG Signal with PSI

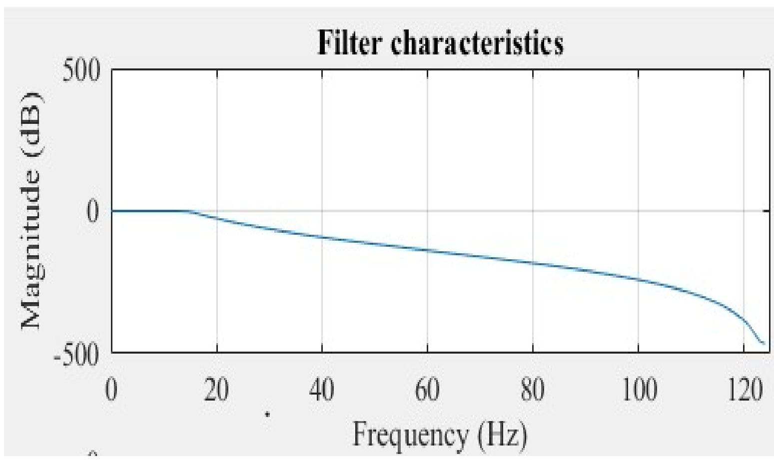


Figure 3.12 Designed Filter Response

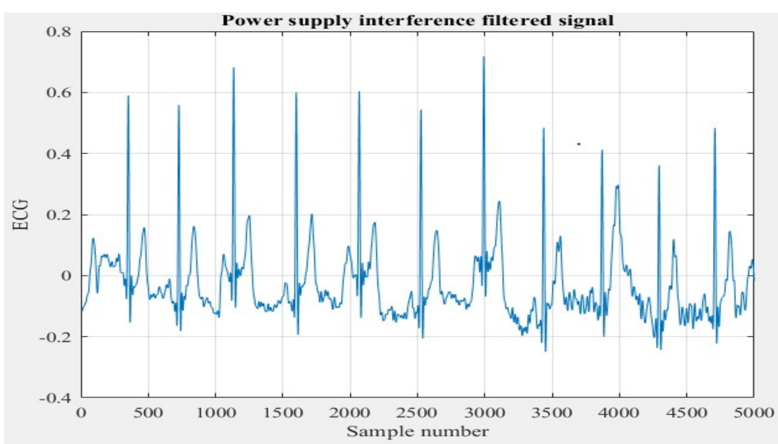


Figure 3.13 ECG Signal devoid of PSI

3.2.3 Low Pass Filtering and Smoothing

The left-over artifacts now after baseline and PSI removal is worked with low pass filtering and smoothing. Butterworth filtering is popular choice to work with here. These filters have the advantages properties such as no surges in its passband and stopband zone, flat maxima response. Other explorable options include usage of FIR and IIR filters for implementing the same.

3.2.3.1 Our Approach for LPF for Further ECG Pre-Processing

With the analysis done with multiple filter setting including notch, FIR and IIR filters, settings used in our experiment are picked as below.

a) W_s = 50 Hz
b) W_p = 40 Hz
c) R_p = 0.1 dB
d) R_s = 25 dB

The MATLAB command "buttord" can create the required filter with above mentioned settings and Smoothing with N=5 is applied.

The same behavior is observed with usage of IIR filters. But the advantage that lies with BW (Butterworth) filter is almost ripple-less passband and same is legitimate for stopband. Equation (6) provide the response function for IIR Filters.

$$H(z) = \frac{\sum_{l=0}^{M} b_l z^{-l}}{1 + \sum_{l=1}^{N} a_l z^{-l}} \tag{3.6}$$

3.2.4 Our Preprocessing Finalized Procedure

The Figure (3.14) below depicts the steps pursued in our setup for acquiring the clean Electrocardiogram signal which will be used in further steps to acquire key traits to be used to form a feature vector for biometric recognition.

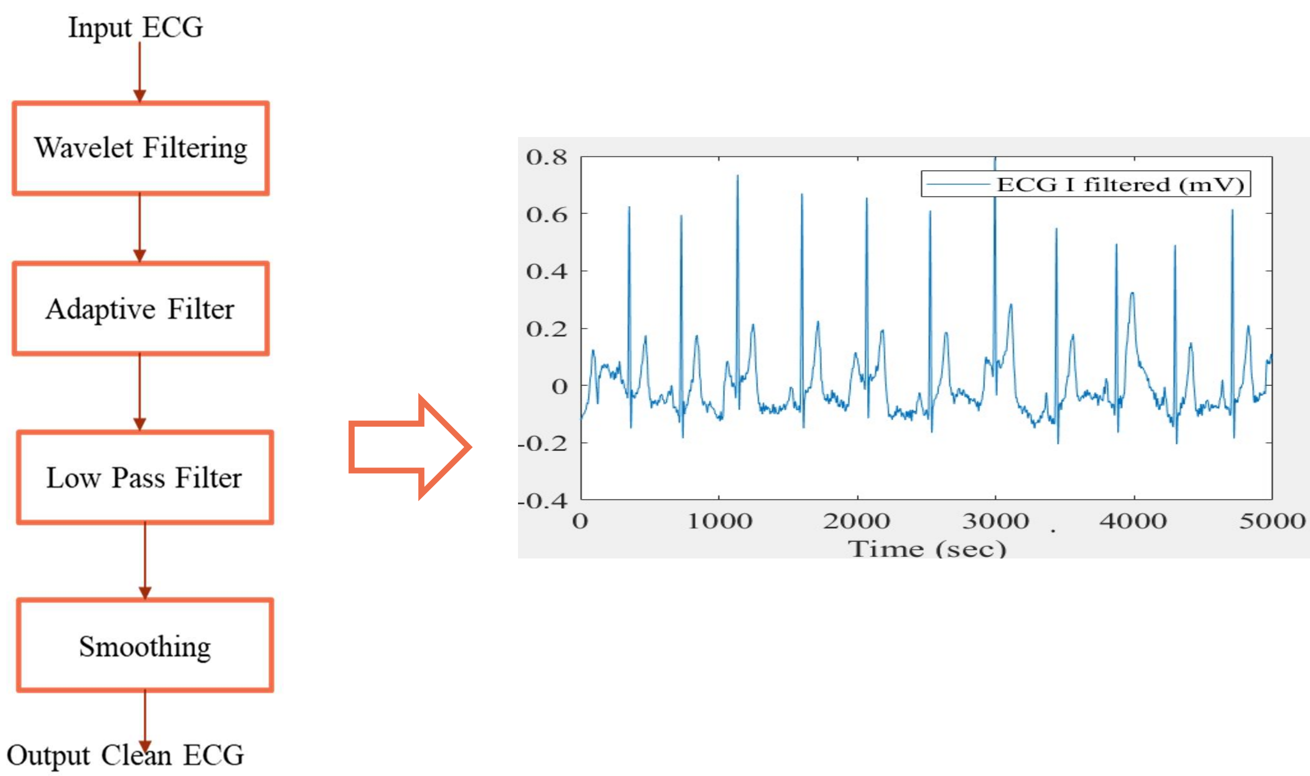


Figure 3.14 Pre-processing of Electrocardiogram Signal and Clean ECG Output

3.3 FEATURE SELECTION AND EXTRACTION FOR ELECTROCARDIOGRAM SIGNAL

In this section of the research, we shall consider the multiple unique traits that could possibly be extracted from Electrocardiogram signal. As detailed in the introduction part, there are various wave parts constituting an Electrocardiogram signal with each wave signifying a specific activity happening inside the heart, occupying a specific part of Electrocardiogram and have a range of temporal and amplitude values of occurrence.

In our study, we have analyzed the fiducial features of Electrocardiogram, including the heart beat and vector corresponding to full PQRST part of the Electrocardiogram. Hence, we first look at details of extraction of variety of available wave points and their traits related to magnitude and time information.

3.3.1 Extraction of R wave

The approaches delved into this study for pin point localization of R wave is based on methodology put forward by Pan Tompkins and another explored approach is based on Wavelet transform. The results of R part temporal values are matching almost perfectly, suggesting any one of these could be used as per ease of implementation.

Let us consider details of both one by one in next parts of this study.

3.3.1.1 PAN TOMPKINS based approach for locating R wave

One of the most sought and accurate analysis for detecting QRS complex and localizing R wave time occurrence is done using the method put forward by Pan Tompkins. The steps involved in this are drafted as below.

a) Implementing bandpass filter via cascade of Low Pass Filter and High Pass Filter

Response for LPF can be worked out from Equation (3.7)

$$y(n\tau) = 2y(n\tau - \tau) - y(n\tau - 2\tau) + x(n\tau) - 2x(n\tau - 6\tau) + x(n\tau - 12\tau) \quad (3.7)$$

Response for HPF can be accounted from Equation (3.8)

$$y(n\tau) = 32x(n\tau - 16\tau) - [y(n\tau - \tau) + x(n\tau) - x(n\tau - 32\tau) \quad (3.8)$$

b) After this, we would calculate the derivative to focus on the slope of QRS.

c) Once we have the slopes to work with, point wise squaring operation is performed to make all values positive. Since when we calculate the square of two values, obviously the resultant difference between squared values will be much larger than the original difference. This means some sort of amplification is happening which is non-linear.

d) After all this we would need to do moving average integration. What this will result is some wave shape is formed and focus need to be on R wave, which is impacted by the size chosen for window shape. This relationship is depicted as
Too wide window size => result may include QRS and T parts.
Too small size window => Numerous peaks or results may be from a single QRS part.
Hence a critical part in resultant authenticity is window size. This is done as suggested per Equation (3.9).

$$y(n\tau) = \frac{1}{N}\big(x(n\tau - (N-1)\tau) + x(n\tau - (N-2)\tau) + \ldots\ldots + x(n\tau)\big) \quad (3.9)$$

e) The temporal location can be located using adaptive thresholding.

The figure 3.15 depicts the details of the discussed methodology. The ease of usage, good localization and very less run times prove to be the positive things in favor of such wider use of this algorithm across world.

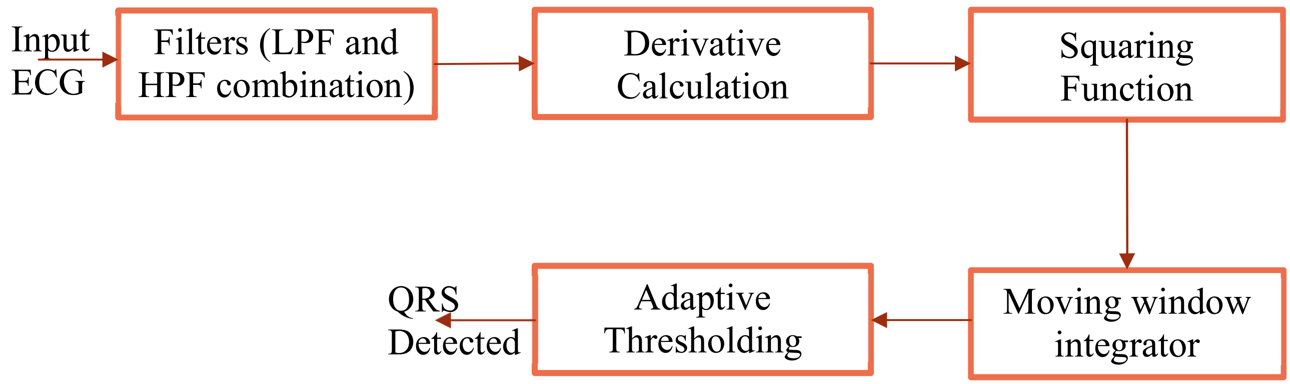


Figure 3.15 PAN TOMPKINS Methodology for detection of QRS complex

3.3.1.2 Wavelet based approach for locating R wave

We have conversed some of the insights of wavelets and wavelets Transform in section 3.2.1 of our proposition. Adding to the details described earlier, first part of the need here is selection of wavelet and then look to work a level of decomposition for this selection. There is no hard and fast rule coded anywhere for choosing a wavelet when it comes to any of the applications but this is totally as per the application. There should be some measure or start point for some traits to consider a wavelet for an application. This is based on the physical properties of wavelets which should be look alike to that of signal to be processed.

Now we need to choose some wavelet similar to the QRS complex and the shape of Duabechies wavelets (dB) inherit the basic physical similarity to QRS with maxima of their energy centered around low frequency zone. We must not lose any of the signal information while doing any kind of transformation, even at least few of the low frequency zone part of acquired signal need to be there, which makes us to do for decomposition level as high as eight.

Fast turnaround time, system design ease, temporal and resolution in frequency zone at the same instant of time and availability of multiple options for acting as basis of wavelet creation make the personals pick this approach when it comes to working with natural or manmade signals. Moreover, the time-changing and transient behavior of these acquired signals make the use of FFT impossible. Even with bifurcating the signal into small numerous parts do not work as this results in loss of simultaneous information about both zones, whether it is temporal or the frequency one. Hence the emphasis in terms of complex and varying signals lies with the wavelet decomposition approach.

Figure 3.16 depict how a signal is divided into numerous coefficients at various levels. We had earlier discussed in section 3.2 about the frequency component division at numerous levels. We observe that the frequency is bifurcated by two at each level, which agrees with the principle of DWT analysis.

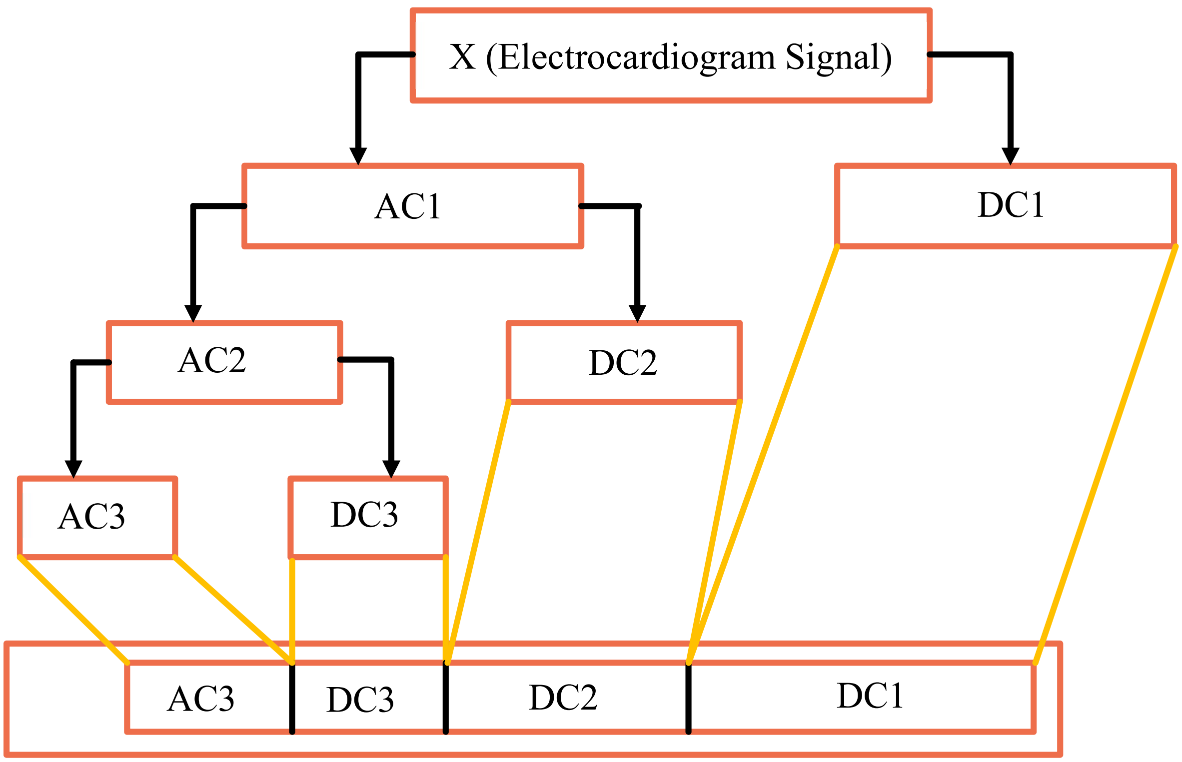


Figure 3.16 Three level Wavelet Decomposition of Signal.

As per the knowledge we have built, as we up the scale value, we would see more and more low frequency zone of the signal and vice-versa, i.e., we go on reducing the scale value or move to lower scales, we get more high frequency zone of the signal. This logic and analysis is fully true in case of Electrocardiogram signal, whenever subjected to wavelet decomposition.

Figure 3.17 and 3.18 depict the behavior of coefficients related to scale of one to four and five to eight respectively. Quite clearly, DC1 is mostly noise in case of Electrocardiogram signal and same is valid for AC8. The shape of waveforms corresponding to level three, four and five matches to that of QRS and hence these are used for localization of QRS in this proposed system.

The method can be examined using the below steps now.

a) Perform db8 up to level value eight.

b) Reconstruct the signal using each level of detail coefficients.

c) Obtain the signal g as per Equation (3.10)

$$g = DC3 + DC4 + DC5 \tag{3.10}$$

d) Perform auto-correlation as Equation (3.11)

$$f = g * g \tag{3.11}$$

e) Do adaptive thresholding to get R peak values.

These values agree with what we have earlier analyzed in 3.3.1.1 section.

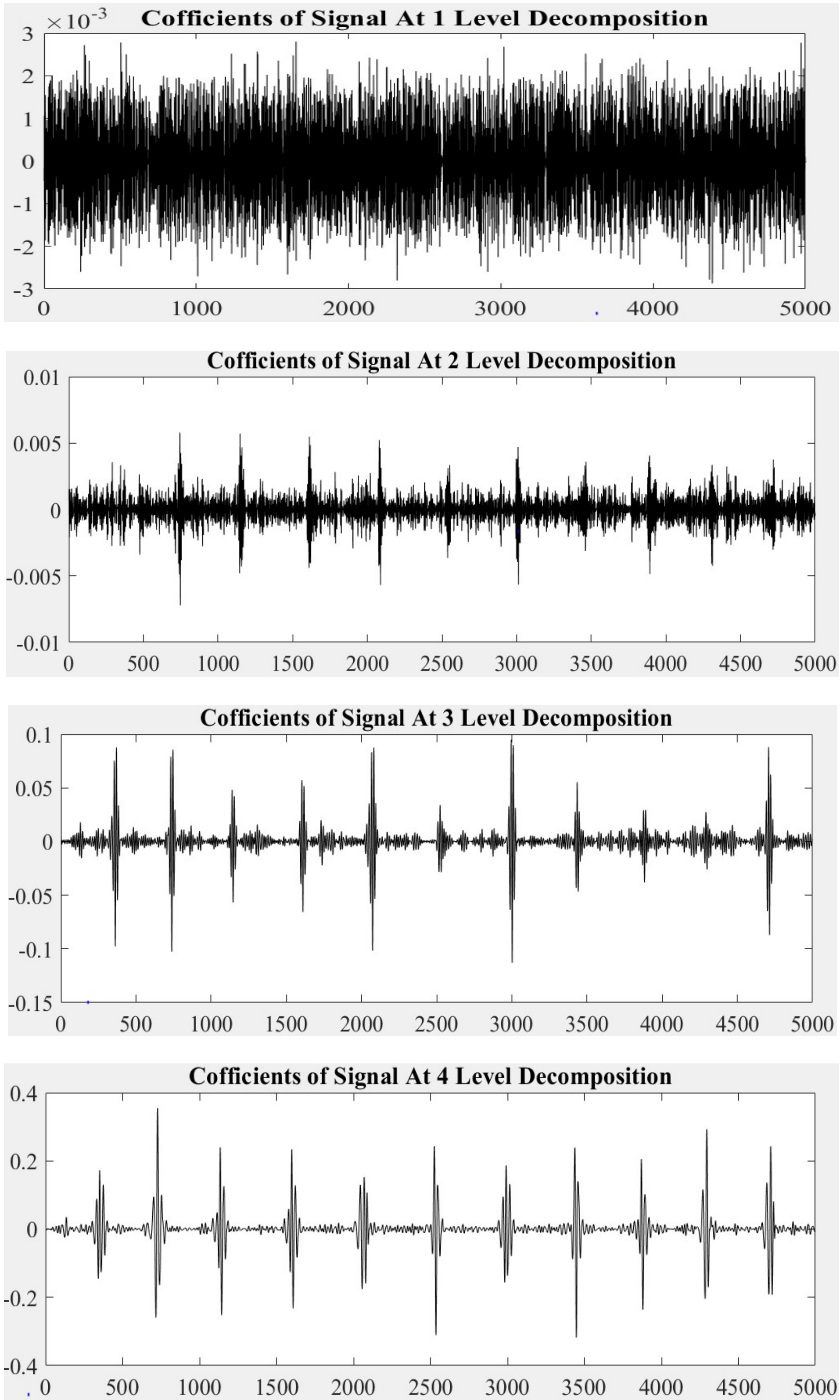


Figure 3.17 Level 1-4 Detail Coefficients (DC1-DC4)

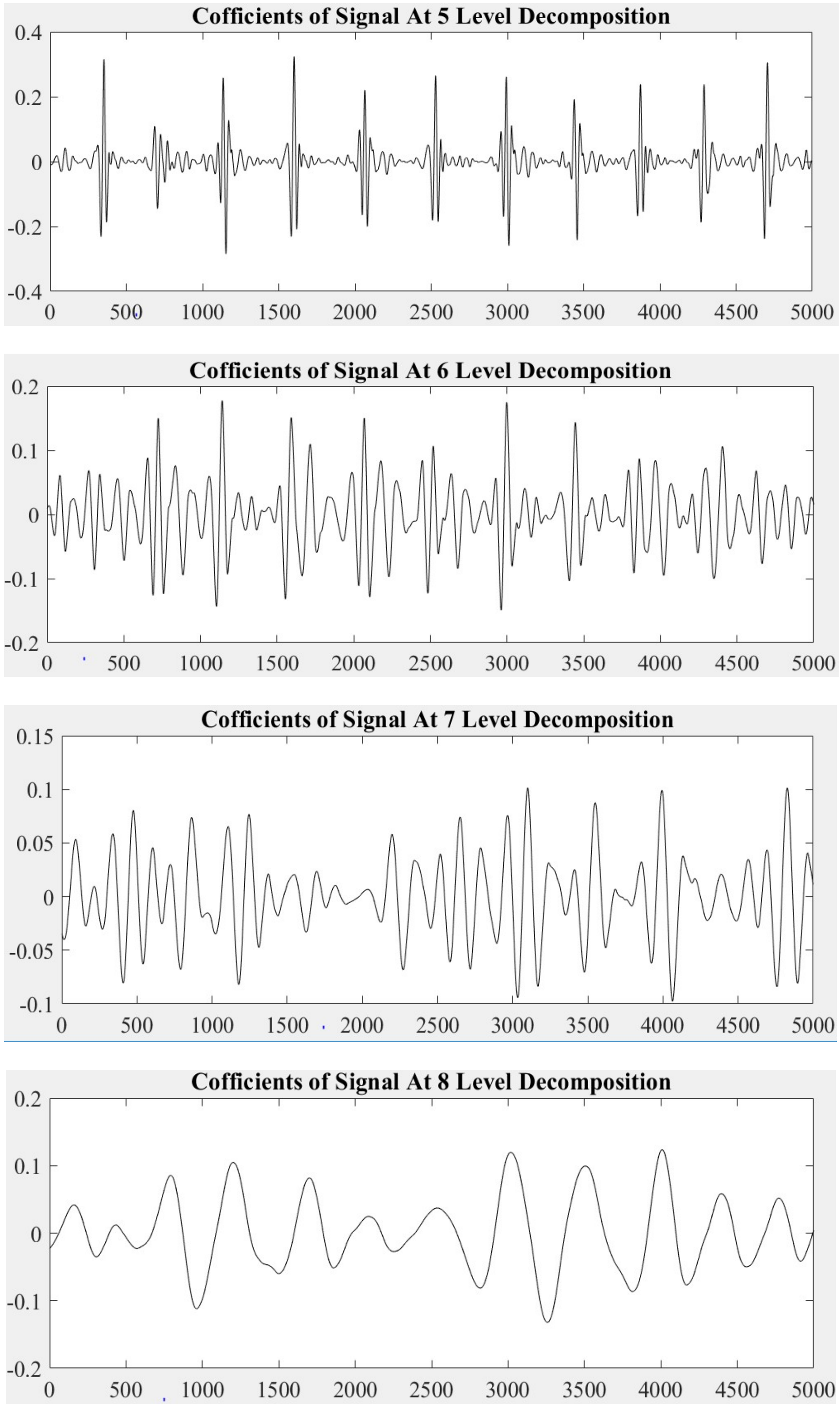


Figure 3.18 Level 5-8 Detail Coefficients (DC5-DC8)

3.3.2 Locating Q and S waves

We shall incorporate the both high and low frequency parts for this. The steps pursued for Q and S detection are as listed below:

a) Obtain signal k as per operations defined in Equation (3.12).

$$k = DC2 + DC3 + DC4 + DC5 \tag{3.12}$$

b) Since the points which we seek lie on opposite side of R peak, so we need to look for mathematical operation ‘differentiation’ performed over five points. The points with maxima magnitude one wither side of zero crossing point, define Q and S respectively.

$$k^{\wedge}(n) = \frac{k(n-2) - k(n+2) - 8k(n-1) + 8k(n+1)}{12} \tag{3.13}$$

3.3.3 Locating peaks corresponding to P and T waves

We shall select DC6 and DC7 to pick up these waves. Obtain a net signal using the operations performed using Equation (3.14).

$$m = DC6 + DC7 \tag{3.14}$$

These all have a peculiar defined temporal zone of occurrence and within this already known temporal zone, we shall look for amplitude peak for localization of these wave points. The same strategy is worked for P wave, i.e., search for maxima within already defined temporal zone.

This finishes all the peculiar point detection schema we have analyzed and now we can detect these points precisely enough to work with.

3.3.4 Analysis of PQRST Segment as a Full Feature Set

To add robustness to our approach, we did consider adding full PQRST segment itself as a part of feature vector set. The results discussed later in this exercise do testify our belief that addition of this full segment should provide more definite results. Other discretions would be to pick up smaller segments like full QRS corresponding to each beat, full PQRS as per each beat as feature set but we did our analysis with the whole PQRST segment per beat as feature set.

The steps for pre-processing have resulted in clean Electrocardiogram Signal and this needs to be further divided into individual beats or segments depicting PQRST parts. Now we shall build over it for analyzing the whole PQRST segment and adding another distinguishing feature for our analysis.

Depending on the physical standing like may be some personal is coming from running, or some other exercise, stress or some temporary medical condition etc, the behavior of Electrocardiogram signal may change. The PQRST full segment length is a variable and needs to be limited for each personal to work with this as a trait vector. Hence, we had fixed this value to be 250 sample long, out of which seventy were taken from left of the R point and 180 were observed from right of R point.

R point is pin pointed using PAN TOMPKINS methodology. Due to the above mentioned multiple causes, there can so happen that we have false detection of R wave as the methodology inbuilt in our used schema is based on putting emphasis on squaring the magnitude. Hence, we have taken care of such cases by putting an interval limit between R points based on the average Heart rate value of the obtained sample. This removes the false R point and add robustness to our analysis. We could observe that there are false R points detected in Figure 3.19 at location around 2700 and 3200, which we have removed from our analysis as per reasoning provided above. Figure 3.19 and 3.20 also depict step by step output of each junction of PAN TOMPKIN methodology.

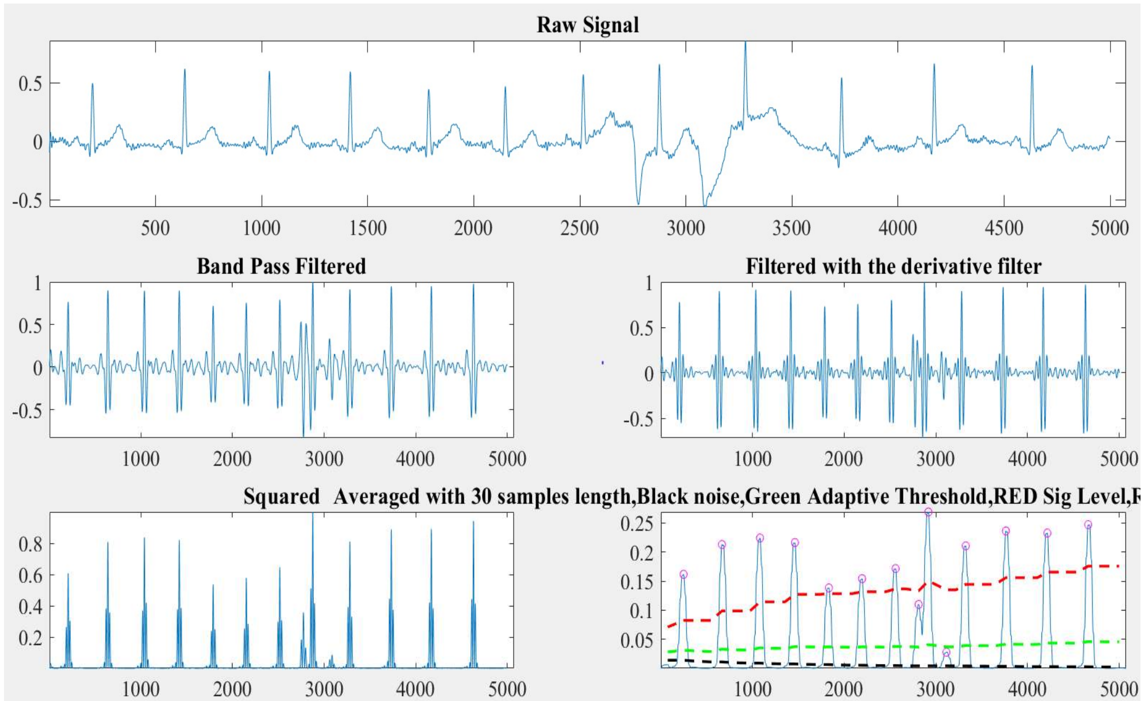


Figure 3.19 R wave Temporal Detection using PAN TOMPKINS (Part 1)

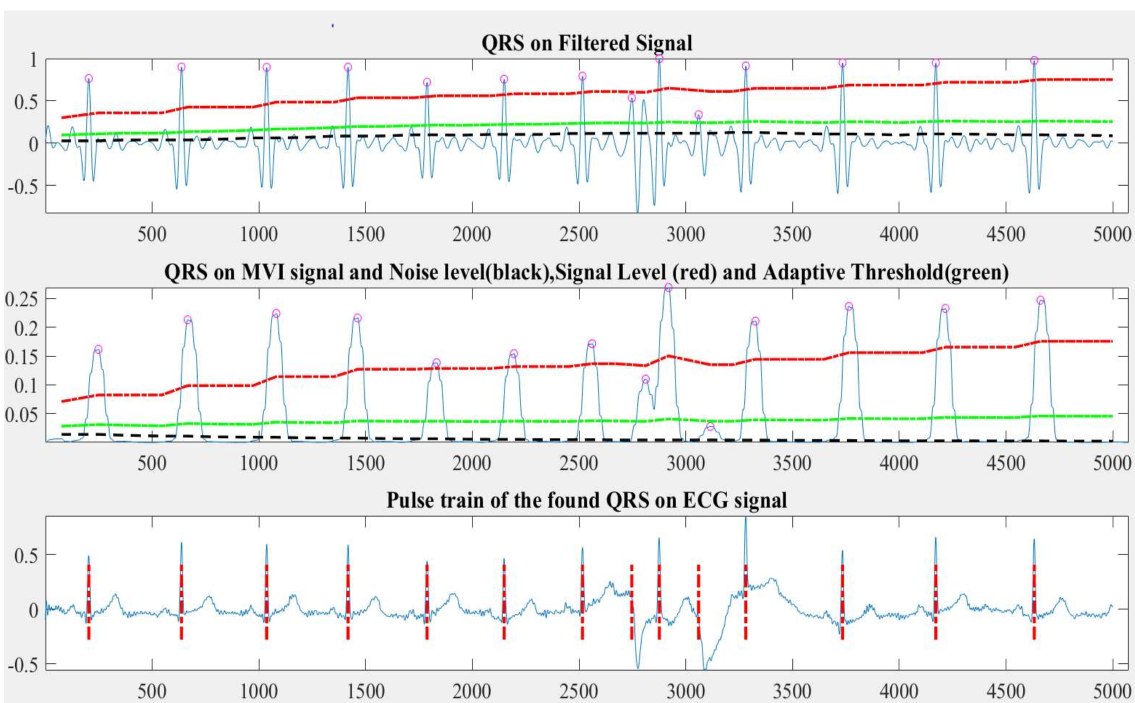


Figure 3.20 R wave Temporal Detection using PAN TOMPKINS (Part 2)

We have extracted nine beats per Electrocardiogram signal, leaving most likely the first and last beat out of each out of analysis, just for the automation to work well. We shall now process these nine beats as follows.

a) Find the mean value of each individual PQRST part and generate a new segment for every beat with the mean value subtracted from the corresponding beat (Figure 3.21).

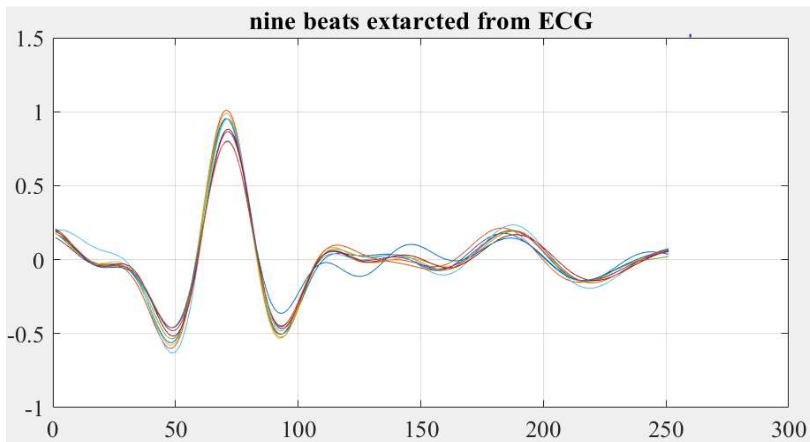


Figure 3.21 250 samples of each PQRST from one ECG sample

b) There may be the case that some of the beats may vary long way than others which may so happen because of artifacts like motion, or may be resultant of respiration or altogether different case of some health condition of personal. Considering this will impact our analysis in wrong way. Hence, we shall take the average of nine beats extracted in earlier step and pick only those six waves for our analysis which have least distance from the calculated average beat. Figure 3.22 depicts this step.

c) Now we have a feature space of 6x251 size since we considered 6 waves and each PQRST has a length of 251. This kind of size is very big since there are more than one Electrocardiogram waves picked for each personal for learning as well as testing purpose. Hence, we will have to have some operation which can reduce the size of our feature space. This is duly performed by Principal Component Analysis (PCA).

Now the next question that needs to be answered is how much of the dimensions are enough to be retained. This is pretty much answered by the magnitude of various eigen values in PCA case.

In our case, we noticed that all the eigen values after five are more or less close to zero and hence we can limit our eigen vector to a dimension of 5 (as we have only first five eigen values as significant contributors).

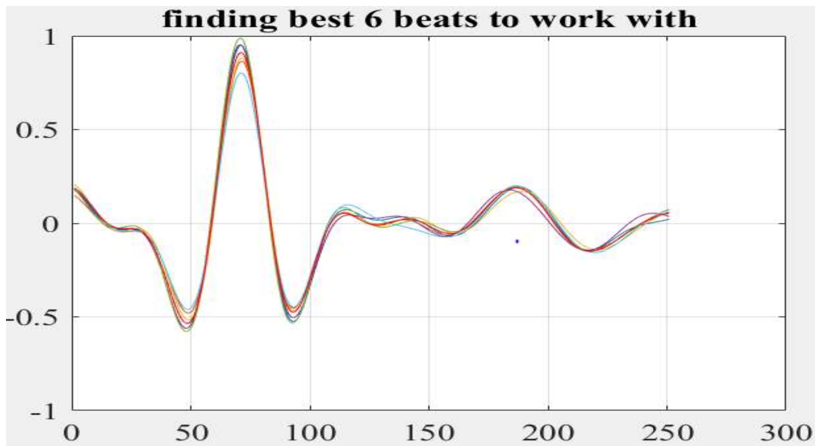


Figure 3.22 Selection of 6 PQRST segments closest to average

Now we have a workable size feature space here and the classifiers can be used to identify the personals.

3.3.5 Final Feature set

We have so far listed everything which we worked out for extraction of various fiducial/temporal points of Electrocardiogram signal. Hence, the feature set based on these temporal points is formed by using various time intervals and magnitudes as duly marked in Figure 3.23. The details of same are documented in Table 3.2.

So finally, we choose 10-dimensional trait vector based on 2,3,5,6,7,8,9,10,11 and 12.

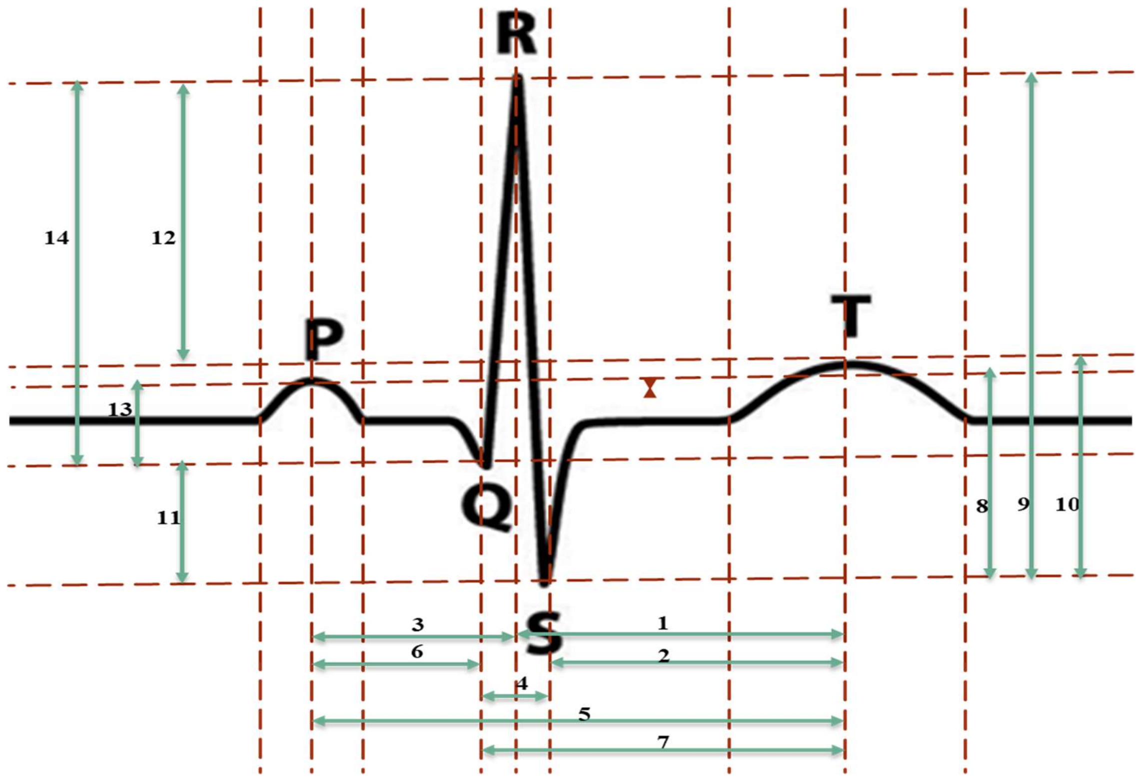


Figure 3.23 Final Fiducial based feature set for Electrocardiogram

Table 3.2 Acquired fiducial Traits of Electrocardiogram

Sr. No.	Description
1	RT Interval
2	ST interval
3	PR interval
4	QRS interval
5	PQRST interval
6	PQ interval
7	QRST interval
8	P amplitude
9	R amplitude
10	T amplitude
11	Q amplitude
12	Difference between P and R amplitudes
13	Difference between P and Q amplitudes
14	Difference between Q and R amplitudes

3.4 CLASSIFIERS

The identification or recognition of a personal can be done once we do classify them and this work is targeted with classification step. Our work does explore couple of classifiers. For the features that include the full PQRST segment as vector, we have explored us of Support Vector Machines (SVM) as a mean to do the classification. The best learning curve does happen with neural networks and neural network does tend to simulate the human behavior up to certain extent. Hence, we have included the Neural network based on radial basis function.

3.4.1 Support Vector Machine (SVM)

The basic aim is to design a hyperplane to separate the classes for Classification. This is an iterative learning classification schema. For the case when the number of classes is limited to two, the figure 3.4(a) depict the classifier property. It is basically a line when only dual class exist.

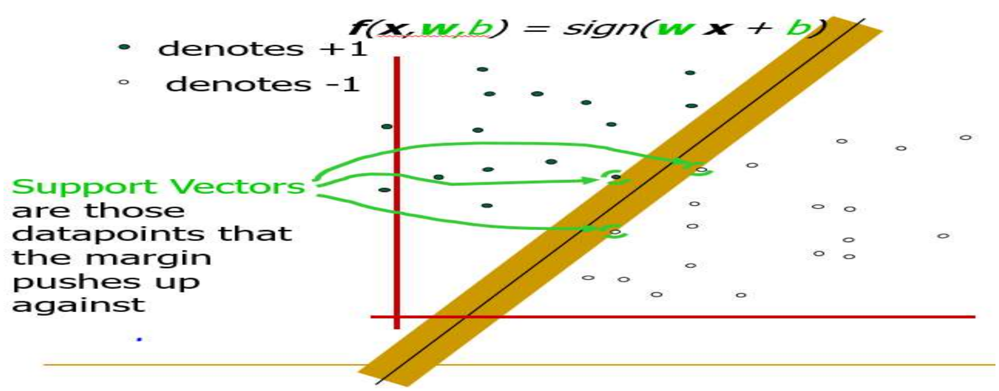


Figure 3.24 SVM for two class

The measure function to signify the efficiency of SVM is as below. This needs to be minimized.

$$\varphi(w) = \frac{1}{2} w^T w + C \sum \varepsilon_i \qquad --- (14)$$

subject to

$$y_i(w^T x_i + b) \geq 1 - \varepsilon_i \text{ and } \varepsilon_i > 0 \text{ for all } i$$

For more than two classes, we need to use Kernel Trick. The kernel function we have used in our analysis is based on Gaussian Kernel which is given by equation (3.15).

$$K(x_i, x_j) = \exp(-\frac{\|x_i - x_j\|^2}{2\sigma^2} \qquad ---(15)$$

3.4.2 Radial Basis Function Network (RBFN)

The basis of this network is the similarity measure between input and the set of inputs that are getting used during training phase of network. The number of nodes at the output stage of the network is equal to number of classification classes. Now the decision function is the maximum score assigned to a class. It is basically performed by weighted sum of every RBF neuron activation values. The standard deviation and mean are computed using K-mean clustering algorithm during training stage to adjust network parameters.

The Gaussian function is given as per Equation (3.16).

$$\emptyset(x) = e^{-\beta\|x-\mu\|^2} \qquad ---(16)$$

The network designed is limned as beneath.

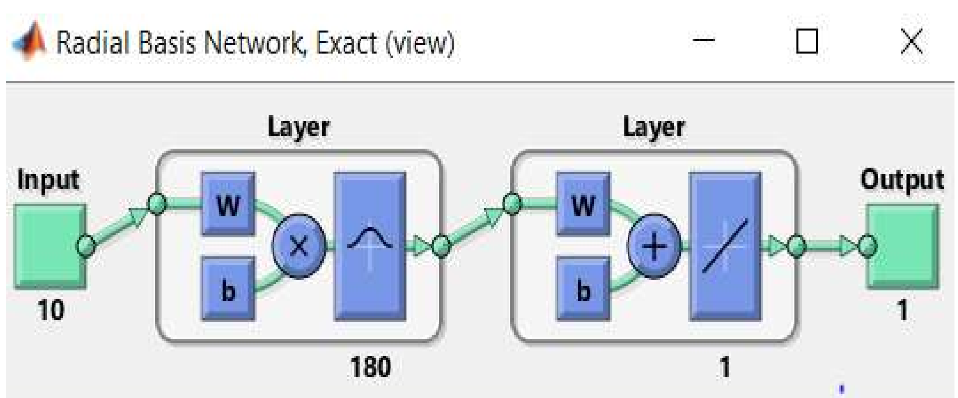


Figure 3.25 RBF based Neural Network

CHAPTER 4

BIOMETRIC FUSION BASED APPROACH

We have merged the face and Electrocardiogram based biometric traits to work out a better recognition rate. The proposed proposition is limned as per Figure 4.1.

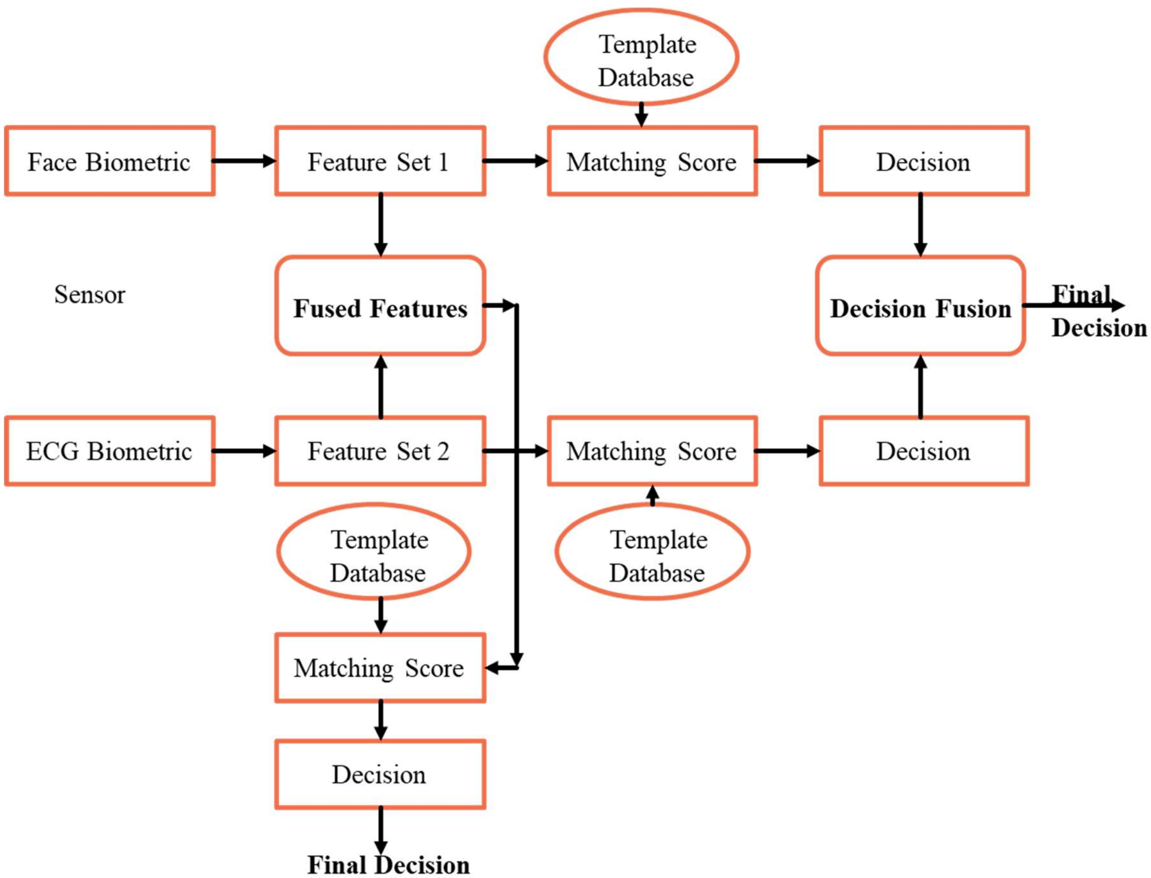


Figure 4.1 Fusion based Biometric System

The fusion based approach can be implemented in two ways as listed below.

4.1 FEATURE LEVEL FUSION SCHEMA

In this schema, we have merged the features related to face and Electrocardiogram traits as first stage itself. This means we need to create a merged feature space before doing any classification. The merging of traits provides a variety to each personal feature and overcome the shortcomings of individual traits. This add robustness to the overall traits. Now the input to the classifier is not the individual traits but the combined trait set. We would use this combined feature set as learning set for the neural network and test features also have the combined traits. The results of the same as discussed in later section.

4.2 DECISION BASED FUSION SCHEMA

In this schema, first the individual traits are analyzed with respect to the separate classifier networks and then the decision from the individual trait recognition network are merged to work out the final identification of the personal.

First step is to perform normalization of individual scores, the resultant of which is to bring individual scores in the range of zero to one. This is required since the output scores of individual traits based schemas may not fall in between zero to one and this will result in a biased decision. This happens due to the case that network with higher numerical score output, which may be correct or incorrect of course, will tend to have a higher say in the final decision-making process, leading to a wrong output situation. Hence, first we bring the individual scores in zero to one range.

Now decision based fusion can be done using below methods.

a) Maxima Voting: This approach is based on maxima voting. The final output is equal to the number with maxima occurrence in fused decision array.

b) Sum rule: This is based on numeric values that are assigned in terms of score of individual personal and then element-wise addition is performed. The outcome or identified personal is the element in array with maximum value. This is a popular approach when the scores are based on distance matrix. This is depicted by operations in equation (4.1).

$$f_i = \sum_{m=1}^{M} n_i^m \,, \forall i \qquad --- (1)$$

4.3 OUR FUSION APPROACH

Our approach has been based on decision based sum rule schema. The biometric schema based on face recognition results in distance matrix as a resultant, which contains distance of the query image from each of the model images. This is normalized to have all values in the range of zero to one. We have termed this as NDM. NDM can be easily found as per Equation (4.2).

$$NDM = \frac{distance\ array}{\max(distance\ array)} \qquad (4.2)$$

In NDM array, we have the matching personal with the least distance associated. Hence, we would need to create Final Distance (FD). This can be performed as Equation (4.3).

$$FD = 1 - NDM \qquad (4.3)$$

Now, the scores from Face trait schema are ready to be merged. Next step is to get the Electrocardiogram trait based schema scores normalized and we chose the probabilistic model approach for this. The output of Electrocardiogram based schema has been matching subject array, hence we create a probabilistic model for every one of these matching subjects as per Equation (4.4).

$$PM(i) = \frac{Number\ of\ occurence\ of\ i^{th} subject}{Total\ count\ of\ array\ resultant} \quad (4.4)$$

For the final score, we can have score fusion (SF) as addition of FDM and PM. Equation (4.5) depicts this.

$$SF = FDM + PM \tag{4.5}$$

The one with the maximum score fusion is the output of the schema. This is duly depicted by Figure 4.2.

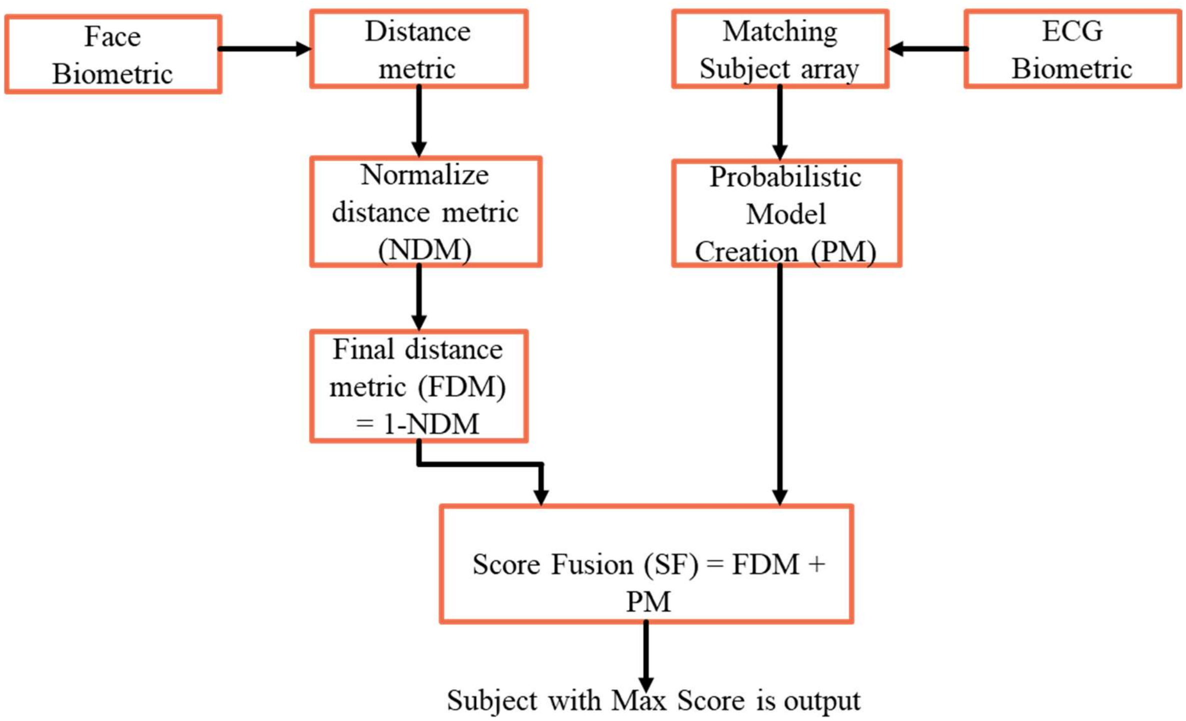


Figure 4.2 Our Fusion Scheme

CHAPTER 5

RESULTS

This section caters to the collation of results. We have used MATLAB R2017b for the implementations and results collation of our schema.

First, we shall look at the results for individual traits based schemas. Then we have listed the results based on fusion of both of the traits.

5.1 DATABASES

We shall utilize the listed databases for individual traits in corresponding sections. Both these databases are available in public domain and picked directly from listed links.

a) Face Database

The described work is established on the Face Db B enlisted by Yale, which has a rich amount of 16128 images, covering nine poses under sixty-four illumination conditions, and this whole database is captured using 28 personals. It can be accessed from here.

Our Experimental Conditions:

- Images catering to only frontal views are chosen.
- Randomly, we have picked 20 subjects to work with out of full set.
- For every personal, only one image is utilized as learning set.
- For the checking of correctness of our schema, the created set of test images consists of a total of sixteen images.

- Before doing any work on the set, we need to ensure that the cardinality of each component of full set, either learning or test, is same. We restricted it to value 192x168.

b) Electrocardiogram Database

The utilized dB is listed as ECG-ID. The full set is public and is accessible from Physionet. The vital points are as enlisted below.

- Rich set with ninety personal records.
- Every Electrocardiogram is acquired for a length of ten seconds.
- No restriction of any kind imposed over personals while acquiring the samples.
- Lead 1 utilized here.
- Randomly, we have picked 20 subjects to work with out of full set.
- For every personal, three Electrocardiogram recordings were utilized for leaning. Actually, every Electrocardiogram is extracted as nine beats and hence, we have totality of eighteen betas to learn for every personal.
- For the checking of correctness of our schema, the created set of test Electrocardiogram consists of a total of two recordings, but since we bifurcate each sample in 9 beats, the net reckoning is 12 test elements for each personal.

5.2 FACE SCHEMA RESULTS

Results based on face as an individual trait are documented with here. Just to set the tone for the variety the schema is already taking care of, we shall start with training full set and then one personal test set.

5.2.1 Training Subjects

Figure 5.1 depict the twenty learning images from different personals. The variety of personals is pretty evident in the set.

Figure 5.1 Face Trait based schema - Training Set

5.2.2 Test set of one personal

The test set of a personal is depicted as Figure 5.2. Frontal aspect is considered here with variance of illumination.

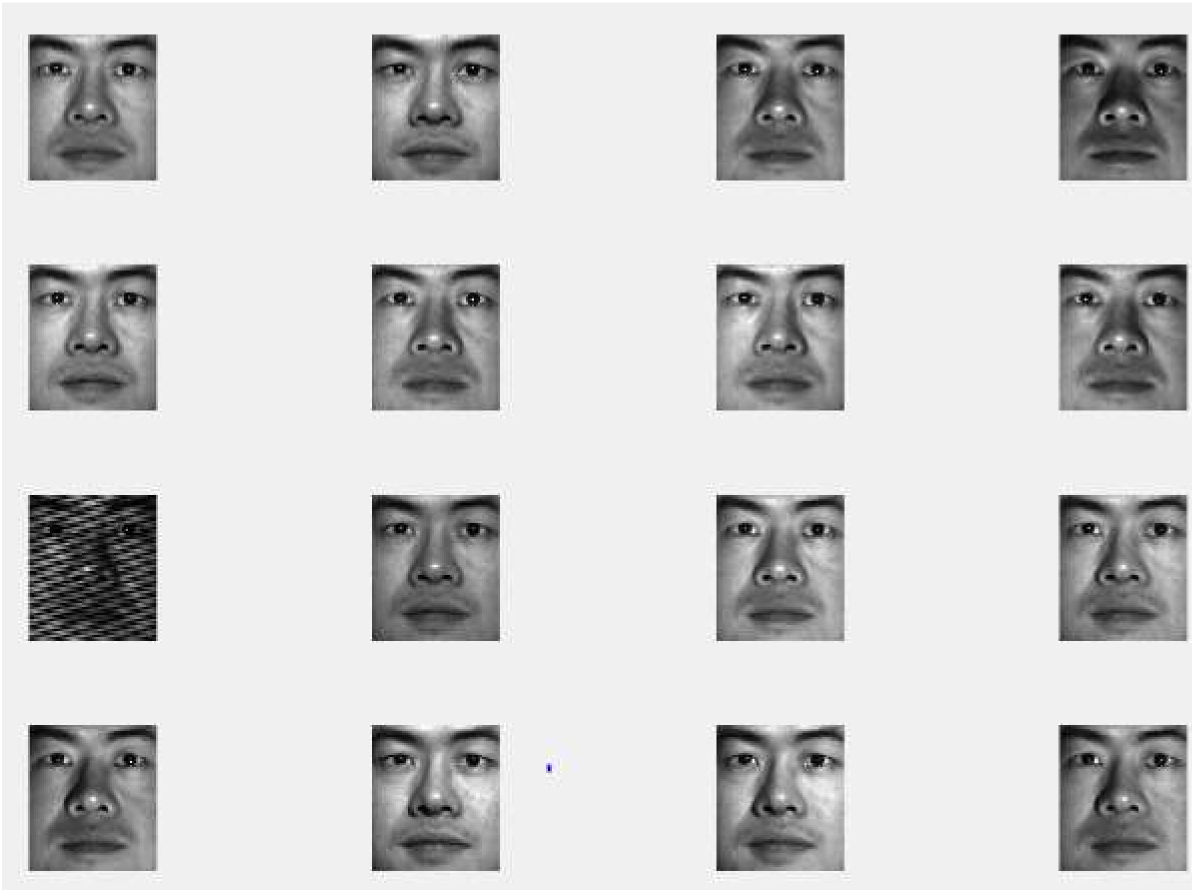


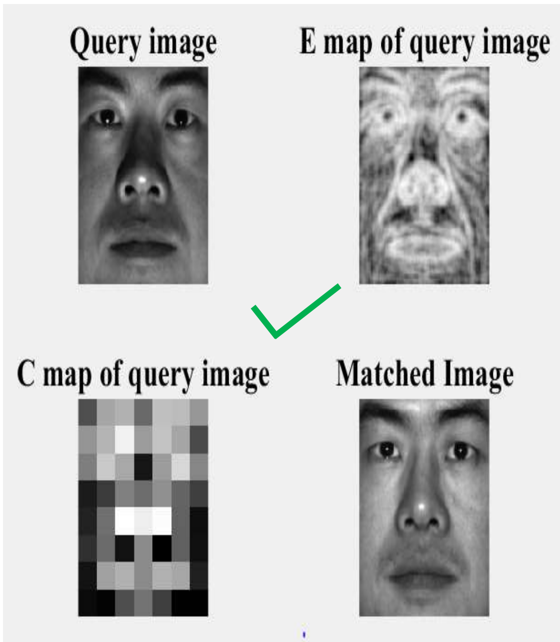
Figure 5.2 Face Trait based schema - Test Set of a personal depicting intensity variation

5.2.3 Sample Results

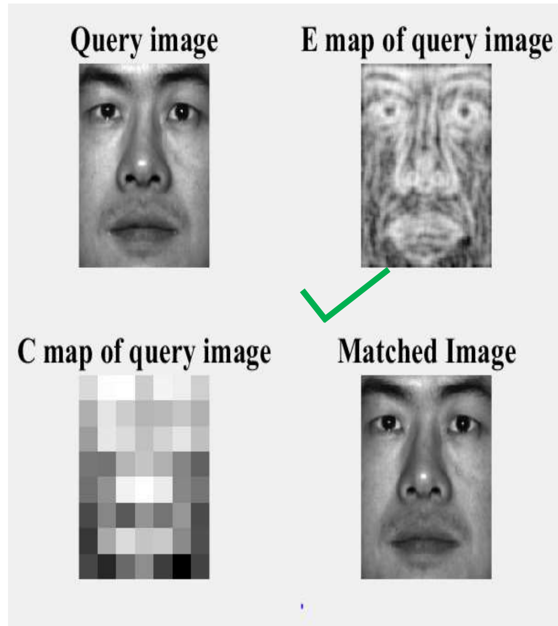
Here we list couple personal examples where the proposed schema results in match and negative in cases shown with viable reasoning.

The Figure 5.3 depict the implementation on personal 2. The first three set show perfect output but the fourth fails for which viable reasoning is dark image resulting in grave difference in C map.

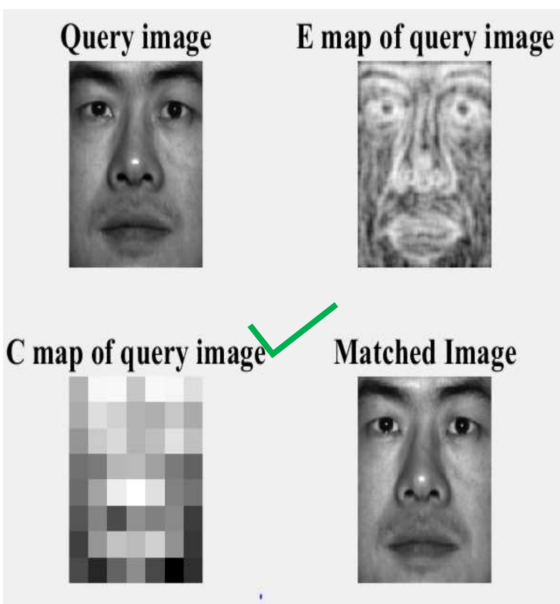
Figure 5.4 depicts the case for personal 9. Again, here the fourth case fails to match. The reasoning is that here the view angle has been modified in test image. So, C map has differences and hence, faulty output.



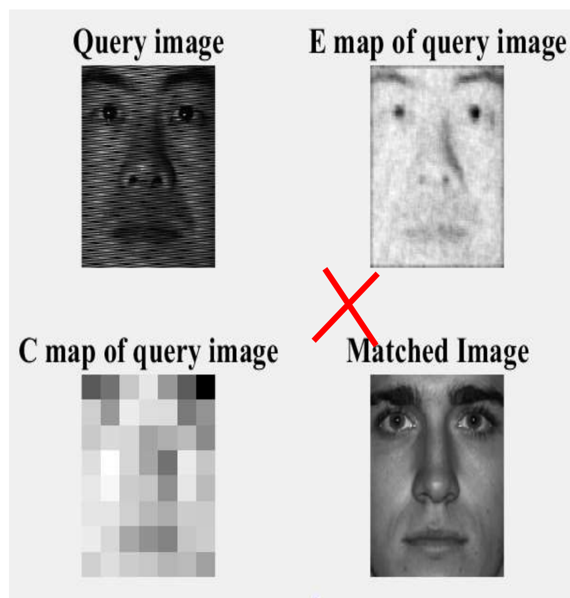
(i)



(ii)



(iii)



(iv)

Figure 5.3 Subject 2: Few Results

Very Dark image (iv) results in an almost flat C map, resultant of which is that while doing weighed distance metric, the C map contribution is negligible and hence, the failure.

(i) (ii)

(iii) (iv)

Figure 5.4 Subject 9: Few Results

The change is view angle disturbs C map, causing mismatch.

5.2.4 Performance Metric for Face Trait based Schema

$$Classification\ Accuracy\ (CA) = \frac{No. of\ correct\ Macthes\ for\ a\ subject}{Total\ test\ set\ of\ a\ subject} \tag{5.1}$$

$$Overall\ Accuracy\ (OA) = \frac{Total\ correct\ matches\ across\ all\ subjects}{Total\ count\ of\ test\ image\ set\ across\ all\ subjects} \tag{5.2}$$

We have done relative study on the PPCA and EWPPCA based methodologies to understand how exactly the entropy weighing helps in proposed Face traits based method. It is evident that EWPPCA is much better when it comes to accuracy metric than PPCA. Figure 5.5 depict this per subject-wise.

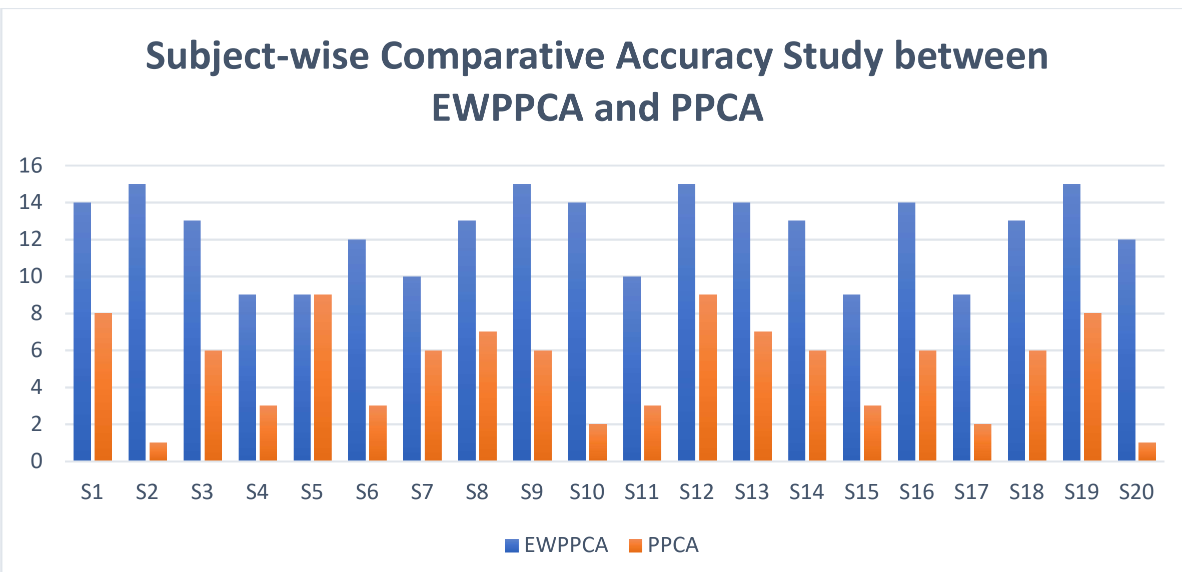


Figure 5.5 Subject-wise comparative analysis between EWPPCA and PPCA

Let us denote OA for EWPPCA as OA_{EWPPCA} and OA for PPCA as OA_{PPCA}.

After compiling results for all test subjects across whole set, we have

$$OA_{EWPPCA} = \left(\frac{248}{320}\right) X100 = 77.5\%$$

$$OA_{PPCA} = \left(\frac{102}{320}\right) x100 = 31.87\%$$

Table 5.1 depicts the summary of these face based traits as analyzed.

Table 5.1 Comparison Results for Face based Schema

Methodology	Training/Test set per personal	Correct Identification	Total subjects	Efficiency
PPCA	1/16	102	320	31.87%
EWPPCA	1/16	248	320	77.5%

Hence, EWPPCA performs much well and we will see results of merging same with Electrocardiogram in next section.

5.3 ELECTROCARDIOGRAM BASED TRAIT SCHEMA RESULTS

As listed in section 3.3.5 for the feature set for Electrocardiogram Signal, we have selected ten fiducial points, five of which are based on amplitude of Q, T, P, S and R waves and residue five are picked as durations between these various temporal points. This is discussed already in detail in section 3.3.5. Also, we had added full PQRST part of the beat as such, which is of 250 sample long. This further boosts the accuracy.

Figure 5.6 and 5.7 depict the fiducial point for couple of Electrocardiogram signals.

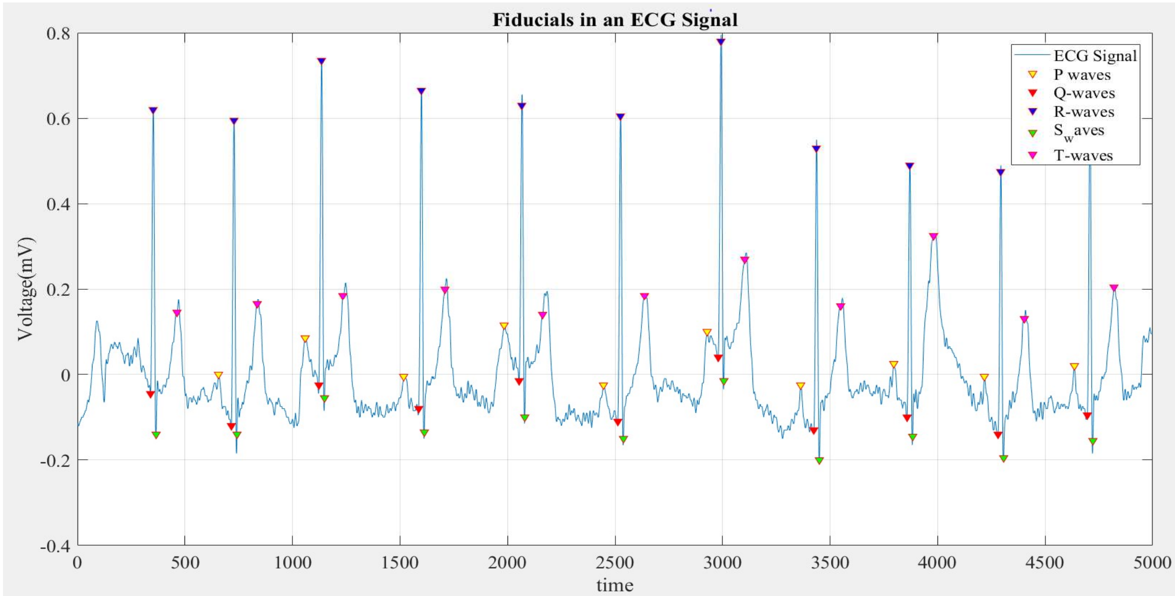


Figure 5.6 Electrocardiogram Fiducial Point Locations (Signal 1)

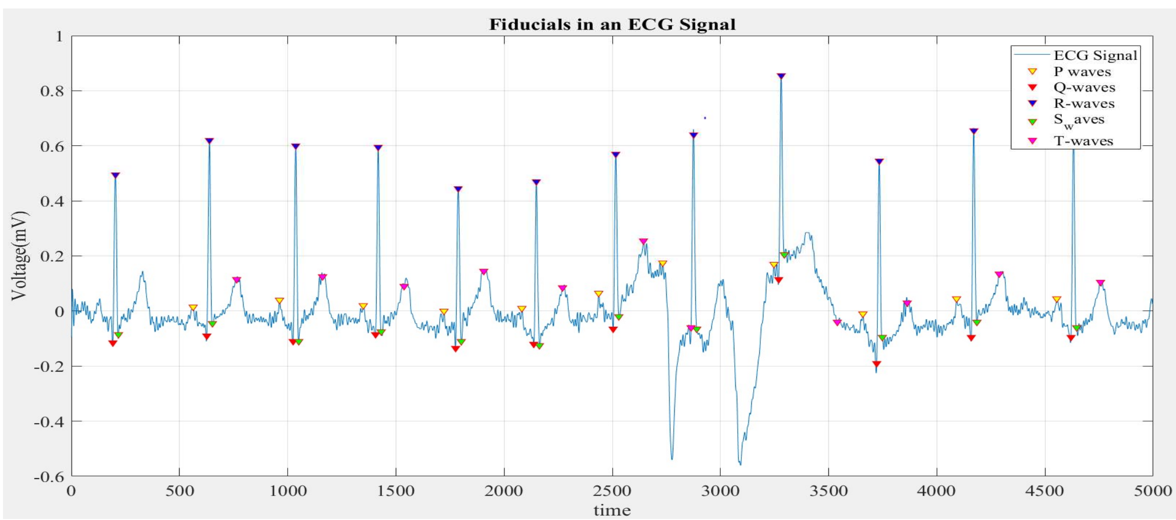


Figure 5.7 Electrocardiogram Fiducial Point Locations (Signal 2)

We can clearly see that in Figure 5.7, there are 2 ill-directing peaks on negative side at about 2700 and 3200 respectively. We have already filtered such wrong peaks which may be acknowledged as R point, which further improved our results.

The metric to obtain the performance of listed schema for Electrocardiogram is marked as Subject Accuracy (SA), which denotes the net percentage of rightfully matched personals.

$$Subject\ Accuracy\ (SA) = \left(\frac{Total\ amount\ of\ correct\ macthes\ across\ all\ subjects}{Total\ test\ set\ across\ all\ subjects}\right) x100 \qquad (5.3)$$

This metric is compared with two methodologies, one with only fiducials taken as feature trait and another with PQRST part embedded with fiducial. The overall stats for relative accuracy and personal-wise comparison is limned in Figure 5.8 and diagram 5.9 and Table 5.2 as below.

$$SA_{fiducial+PQRST} = \left(\frac{207}{240}\right) x100 = 86.25\%$$

$$SA_{fiducial\_only} = \left(\frac{190}{240}\right) x100 = 79.16\%$$

Table 5.2 Results Comparison for ECG Schemas

Methodology	Training/Test set per personal	Correct Identification	Total Subjects	Efficiency
Only Fiducial based ECG traits	18/12	190	240	79.16%
Fiducial +PQRST based ECG traits	18/12	207	240	86.25%

The resultant of this analysis has stated that PQRST part needs to be embedded with the temporal and fiducial points to enhance the ability of the overall schema, which we have followed in our analysis while doing fusion of the two traits – one based on Electrocardiogram and other on Face traits.

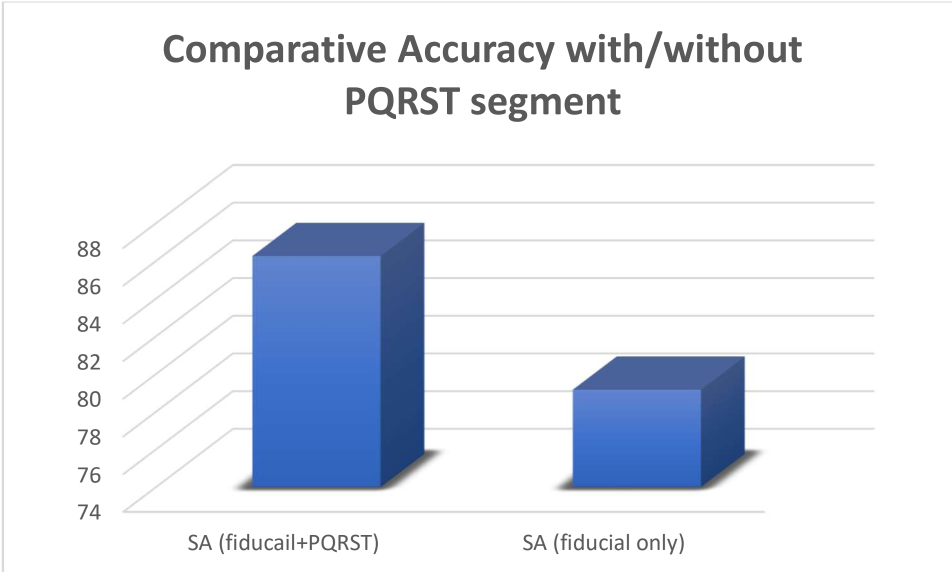


Figure 5.8 Overall Comparison for with/without PQRST part for Electrocardiogram Schema

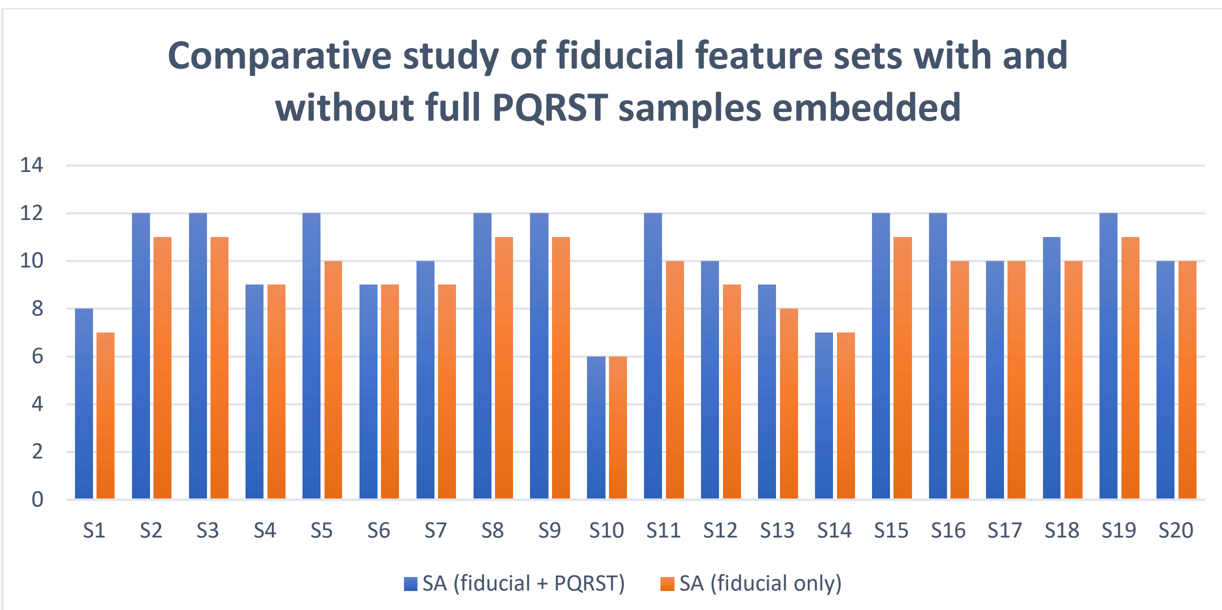


Figure 5.9 Personal-wise comparison for with/without PQRST part for Electrocardiogram schema

Another good analysis point would be to see where most of the personals are getting misclassified. This can be evident once we dump and analyze the confusion matrix. We have looked for 10 subjects to analyze this and see the proposed schema confuses wrong matches when the age and sex of personals does exhibit match.

Figure 5.10 depict the confusion metric for 10 subjects, just for analytic study.

```
>> confusion_matrix

confusion_matrix =

    0.6667    0.3333         0         0         0         0         0         0         0         0
         0    1.0000         0         0         0         0         0         0         0         0
         0         0    1.0000         0         0         0         0         0         0         0
         0         0         0    0.7500    0.2500         0         0         0         0         0
         0         0         0         0    1.0000         0         0         0         0         0
         0         0         0         0    0.0833    0.7500    0.1667         0         0         0
         0         0         0         0         0    0.1667    0.8333         0         0         0
         0         0         0         0         0         0         0    1.0000         0         0
         0         0         0         0         0         0         0         0    1.0000         0
         0         0         0         0    0.5000         0         0         0         0    0.5000
```

Figure 5.10 Ten personal output confusion Matrix

5.4 OUR FUSION SCHEMA RESULTS

The results are captured in terms of Subject Accuracy (SA) again. Here we have score merging to work out a hybrid fusion based biometric schema.

For the Electrocardiogram and face databases, we have done purposeless assignment of a set of Electrocardiogram waveform set to a set of Face sets. This has helped us achieve a dataset with twenty sets of Electrocardiogram and Face sets. Out of every set, one face and 18 beats were used for learning of the classifier and rest of the image set of sixteen and twelve beats has been as test intent. So, we verify all permutations each test image with all Electrocardiogram samples of the respective personal and see how many of these prove to be accurate for personal’s identification. For the below results compilation, we have pursued the practice based on cross-validation. This has made the test set much wider, each of whose combinations have been verified with neuron network.

Table 5.3 depict the comparative summary of all methods we explored.

Table 5.3 Comparative Study Summary

Sr. No.	Biometric Methodology	Biometric Trait used	Accuracy
1	PPCA	Face	31.87%
2	EWPPCA	Face	77.50%
3	Electrocardiogram based on fiducial but not PQRST interval	Electrocardiogram	79.16%
4	Electrocardiogram based on fiducial and PQRST interval both	Electrocardiogram	86.25%
5	Our Fusion method (Combine 2 and 4 as Features)	Face and Electrocardiogram	94.53%

$$Subject\ Accuracy\ (SA) = \left(\frac{Total\ amount\ of\ correct\ macthes\ across\ all\ subjects}{Total\ test\ set\ across\ all\ subjects}\right) x100 \qquad (5.4)$$

$$SA_{FUSION} = \left(\frac{605}{640}\right) x100 = 94.53\%$$

Figure 5.11 depicts the comparative scrutiny of all the individual trait schemas with the proposed fusion schema. Figure 5.12 depict the subject-wise comparison between all schemas.

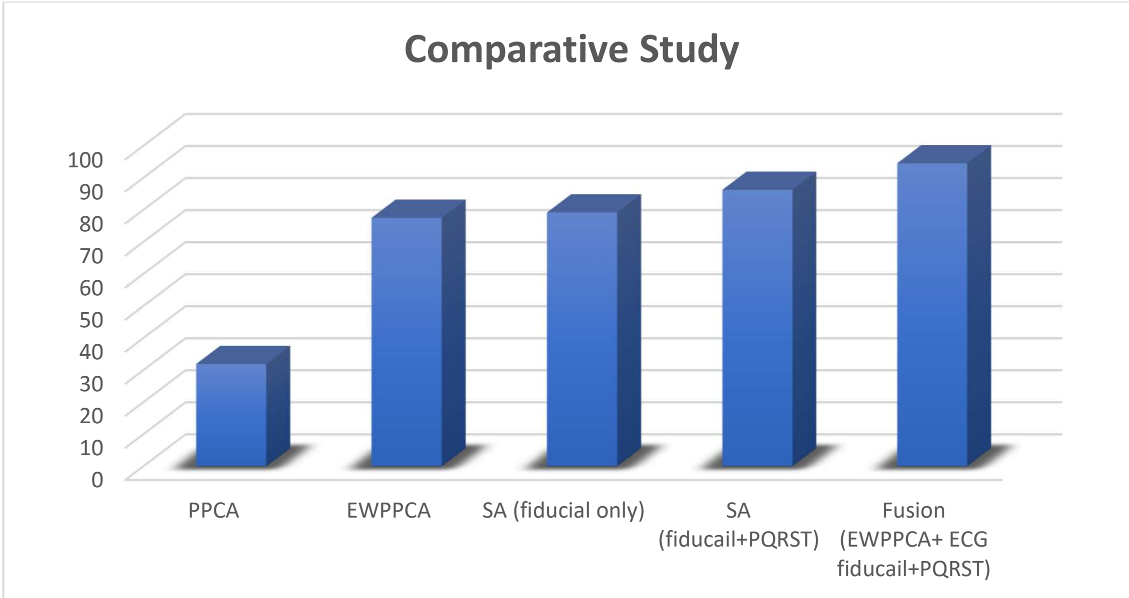


Figure 5.11 Comparative Study of all Schemas explored.

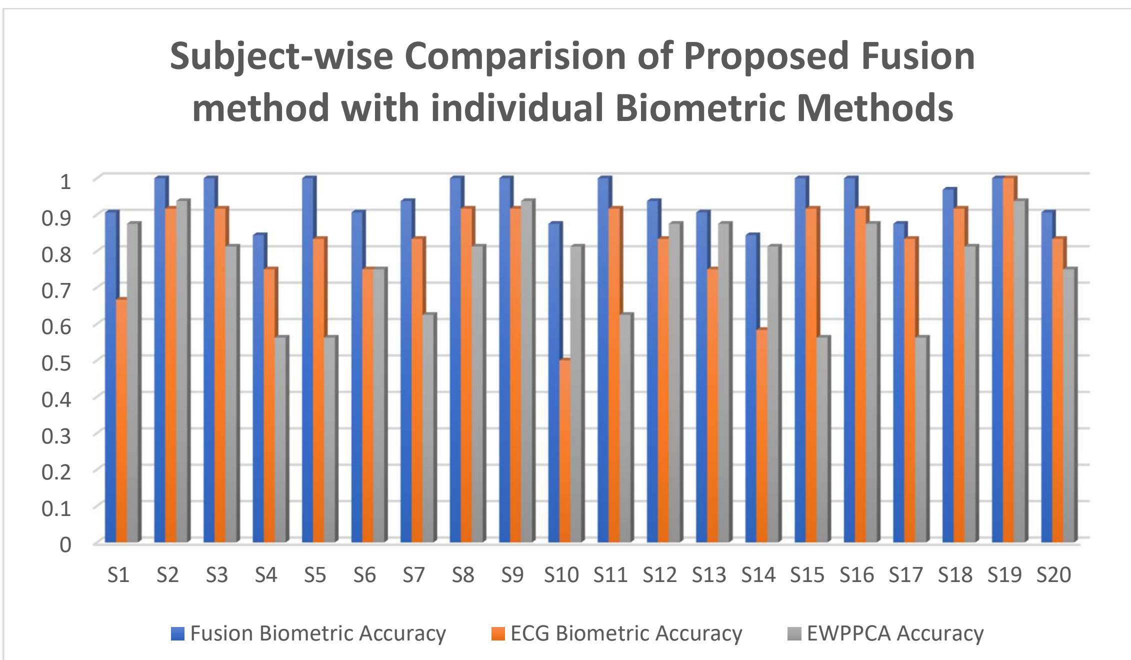


Figure 5.12 Subject-wise relative study all three methods

The personal-wise relative performance of each the schemas, those based on single trait and one with the merged traits based hybrid schema, as in Figure 5.12, shows that fusion of these traits increases the definiteness and is robust.

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1 CONCLUSION

The discussed endeavor based on merging of the two biometric traits (Electrocardiogram and Face traits), demonstrates the efficiency and validity of our proposed schema. The proposed schema has a more robust way of fusing the scores based on single traits. Also, the blending of diversified traits, each of whose brings an individualistic feature for exploiting, marks its own positives and is much better schema in place. Digging deep into heterogeneous procedures, either for drawing up the feature set or allocating these to available classes, has worked out paramount combination, resulting in much exceeding accuracy than individual trait equivalent proposals.

6.2 FUTURE WORK

The discussed endeavor has shown the effectiveness and exceeding correctness of our proposed schema. Supplementary endeavors based on thermal images can be explored to merge with Electrocardiogram traits, bringing another dimension to table with unmistakable features, resultant of which will be superior accuracy. Correspondingly Electrocardiogram traits have been temporal and fiducial, where we can further be appended with WDM and other more temporal points. This will make our schema more fool proof for physiological variations and mutations due to pathologies in these signals. User can build to exploit more consolidation of classifiers to find exceeding combination and results. Hence, embracement of more fiducials, 4-D face traits etc., is area to exploit further.

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