Thesis Report

Improvement in ECG based Biometric Systems using Wavelet Packet Decomposition (WPD) Algorithm

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A thesis submitted in partial fulfillment of the requirements for the degree of MS Robotics and Intelligence Machine Engineering.

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Declaration

I hereby declare that I have written this thesis titled as *Improvement in ECG based Biometric Systems using Wavelet Packet Decomposition (WPD) Algorithm* completely on the basis of my personal efforts under the sincere guidance of my supervisor Dr. Syed Omer Gilani. All citations with references to all sources used in this thesis have been mentioned clearly and contents of this thesis have not been plagiarized. I certify that this work contains no material which has been accepted for the award of any degree, or in any university or any previously published material except where due references have been made in the text.

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Language Correctness Certificate

This thesis has been read by an English expert and is free of typing, syntax, semantic, grammatical and spelling mistakes. Thesis is also according to the format given by the university.

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Copyright Statement

Acknowlegements

In the name of Allah, the Most Gracious and the Most Merciful.

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Abstract

In this thesis, a non-fiducial approach based on wavelet packet decomposition (WPD) algorithm for repeated examination of solitary lead electrocardiogram (ECG) for individual identification is planned and tested. Multiple samples of ECG wave are extracted considering R-peak as a reference and WPD algorithm is applied for feature extraction. This feature file is fed as an input to a machine learning classifier i.e. random forest in order to classify the individuals. In this work, records from publicly available MIT/BIH arrhythmia dataset have been utilized to evaluate the proposed system. Best result relies on third level of wavelet decomposition using Daubechies wavelet to analyze the signal. Furthermore, ranker search method is used in conjunction with relief attribute evaluator for feature selection and random forest classifier is applied by generating 100 trees. It is shown that the method is effective for quantifying the classification of arrhythmia ECG signals with accuracy of 92.62 %.

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Chapter 1

Introduction

The measurement of a small changes in electrical potential on the surface of the skin is called an electrocardiogram ECG. It is generated due to the cardiac muscles depolarization and repolarization. In 1924, Einthoven a Dutch scientist for the first time discovered the mechanism of the ECG and he got a Nobel prize for his work [1].

Although every individual have the same prototype of heartbeat as shown in Figure 1.1, but there is quite variance in the detailed shape of the heartbeats i.e. QRS complex P and T wave of ECG are particularly recognized as the most exclusive marks among them. This distinctiveness in ECG revealed its capacity for identification of individuals. Apart from that ECG signal gives crucial information about physical situation of heart along with numerous disorders associated to cardiac conditions. Therefore, the ECG beats in different individuals have some distinct features from one another.

As identification and verification are implicit and explicit claim of identity respectively [2]. ECG based biometric system are capable to provide swift, user-friendly, accurate, valid and inexpensive technique for identification and verification. Moreover exploiting this technology for identifying people offers some unique advantages i.e. ECG contain inherent information about the liveliness of the subject which conventional biometric systems donâĂŹt have [3]. This property makes it nearly unfeasible to temper and deceive. In 2001, Biel et al, revealed that every individual has unique ECG features that might be utilized as a trait of biometrics. They obtain ECG data via electrocardiogram measuring devices and collected amplitude of ECG signal to compare features. However, it depends upon performance of signal processing techniques for noise or artifact removal and feature extraction. In proposed method of identification we used wavelet packet decomposition

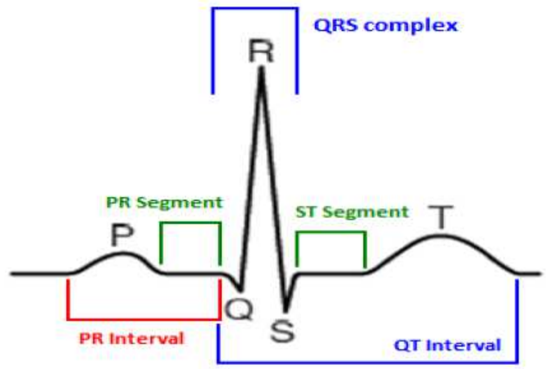

Figure 1.1: Prototype of ECG Waveform

based features and random forest classifier [4].

1.1 Motivation

Due to rapid advancement in technology our daily life is becoming more dependent on automatic and accurate identity proof systems. At present, credentials forgery is the most common and important flaws of the systems based on biometrics. Tokens, smart cards, ID cards, physical keys etc. being used for human identification might be misplaced, pinched, copied, or forgotten at home. Moreover, there are chances of forgetting, hacking or observing the passwords [5]. Besides, people have to recall a large number of passwords and personal identification numbers (PINs) for e-mail accounts, wireless phones, bank ATMs, computer accounts, web sites and so forth. Conventional entity and knowledge based biometric systems raises security concerns regarding the risk of identifying spoofing attacks. Several identification mechanisms have been studied in the past based on physical features [6] such as face, ear, iris, finger prints, face, hand geometry and behavioral characteristics [7] that include gesture, signature, voice, key stroke as well as biological signal characteristics such as ECG [8]. However, physical features and behavioral characteristics can still be falsified, stolen, forged, imitated and copied [9]. Face detection system can be fooled by a photograph, fingerprints can be reproduced, contact lens can easily doge iris recognition system, passwords can be observed, forgotten or hacked and sound can be imitated or preprocessed [10]. Implementing ECG based biometric systems

exhibit some unique advantages over conventional biometrics i.e. it is difficult to falsify and also provides proof for aliveness of the subject [8].
Correct and reliable person identification and verification is becoming inevitable and greater research is needed in biological biometrics due to its requirement for the development of fool proof security systems. Therefore, this technology is considered as the bottom line of highly protected recognition tools.

1.2 Scope and Objectives

ECG is one of the aid for identification of a person due to the prime issue of security lacks in our country. Therefore, ECG domain and research in this field will have advantages in both the recognition and identification systems and will fill the research and industrial gaps. Following are the objectives of this research:

- To advocate individuality and worth of ECG as feasible biometric system as compared to alternative biometric techniques.
- To propose and produce an ECG based automated system for individual identification.
- To discuss the common characteristics of a biometric system.
- Comparison among cutting edge techniques of feature selection, feature reduction and classification on same database.
- Proposed system was evaluated on publicly available database for comparison with prior techniques used by different researchers in literature and to develop biometric applications for real world environment with cardiac irregularities and large population database.
- Single lead data is used in proposed identification system to reduce acquisition complexity and to make the system robust by reducing the time for signal acquisition and training.
- To create a research environment in the field of ECG based biometric systems in the educational institutes of Pakistan.

1.3 Challenges

Along desirable features provided by ECG based biometric, there are some important challenges that need to be addressed while presenting ECG as a robust biometric solution. The proposed system has following challenges:

1.3.1 Pre-processing of Data

The ECG database of MIT-BIH arrhythmia is used to provide data for this research. Both the analog and digital data acquisition devices contain peculiarities that cause their vulnerability to noise. The noise might have of different types such as random, white noise with zero coherence, and coherent noise that are added by the mechanism or proposed algorithms for processing. The first challenge is to remove the noise present in this database by applying pre-processing techniques in order to make it appropriate for further processing. It is accomplished after the analysis of the event occurrence within a particular ECG waveform section.

1.3.2 Feature Extraction

Second challenge in our research is the process of feature extraction. There are number of distinguishable features present in an ECG signal based on temporal, spectral and time-spectral domain features, which might be utilized for the individuals classification. The aim of feature extraction step is to extract fiducial or non-fiducial features for proper identification and verification.

1.3.3 Feature Reduction

The prime challenge of this research is to discard the inadequate and worthless features from a pool of available features for the improvement of results. We are using ranker search method in conjunction with relief attribute evaluator to determine the set of best features to achieve the mention goal.

1.3.4 Classification

Classification of features is the other challenge in this research. The classifier used for the classification purpose is called random forest classifier. A feature set of labeled training data is fed to the machine learning classifier and the system is trained to classify the individuals.

1.4 Thesis Structure

Following is the format of rest of the thesis: Chapter 2 contains introduction to biometrics, classification to biometrics, challenges and how ECG is acquired. Chapter 3 presents an introduction to electrocardiogram gives overview of heart anatomy, ECG as biometric and comparison of the previously designed algorithms and methods and summarizes the accuracies of certain algorithms. Chapter 4 covers the literature review of the ECG based biometrics. Chapter 5 contains the main design and methodology proposed for the system. Chapter 6 have results obtained from the experiments and then discussion is done on these results. Chapter 7 contains the conclusive points and the future perspectives of the proposed automated system.

1.5 Summary

Due to rapid advancement in technology our daily life is becoming more dependent on automatic and accurate identity proof systems. Conventional entity and knowledge based biometric systems raises security concerns regarding the risk of identifying spoofing attacks [3]. ECG based biometric system are capable to provide swift, user-friendly, accurate, valid and inexpensive technique for identification and verification. Moreover exploiting this technology for identifying people offers some unique advantages i.e. ECG contain inherent information about the liveliness of the subject which conventional biometric systems do not have [5]. The smaller measurement of potential on the skin surface is called an ECG. The repolarization and depolarization of cardiac muscles generate this electrical activity. ECG acquisition devices are used for capturing this activity. Therefore, an ECG based identification system along with several signal processing and machine learning approaches can be designed in an efficient way. The proposed system has the following blocks: preprocessing, feature extraction, feature reduction, and feature classification.

Chapter 2

Introduction to Biometric Recognition

Biometrics indicates metrics associated to individual human being. These systems are also considered as a recognition tool to perform individual identification and verification on the basis of their biological and physiological characteristics by means of some statistical or pattern recognition algorithm. It is considered as a protected system for the identity verification in an automated style.

2.1 Significance of Biometrics

Benefits of using biometrics are listed below:

- Enhance security - Offer a convenient and inexpensive extra layer of security.
- Decrease deception by utilizing technologies and resources that are difficult to forge. For example, decrease the chance for ID fraud, buddy punching.
- Eradicate those problems resulted due to lost, IDs swapping or passwords forgetting because of the biological characteristics. For instance, the loss of illegal and stolen used of ID cards is prevented.
- Decrease overheads caused by paperwork and password management systems.

- Substitute passwords that are difficult-to-remember that might be attackable, observed or shared.
- Incorporates a huge variety of technologies and biometric solutions, consumer databases and applications into a fast and robust controlled solutions for facility and access to network.
- Provide the automatic facility to know WHO did WHAT, WHERE and WHEN.
- Offers useful savings of cost or increasing return on investment (ROI) in areas like prevention loss or time and attendance for ensuring the efficiency of workable environment.
- Explicitly association of a person to an event or transaction.

2.2 Biometric Applications

Following are some common application of biometrics in different areas.

- **National security:** In a country like Pakistan where terrorism is a big threat to national security and access control to nuclear weapons and border control. Military and police Applications and reliability in criminal and forensics intelligence and investigation.
- **Network security:** Currently, those companies which are working in the networking field have realization about the benefits of biometric authentication for networks and products are offered for achieving this scheme.
- **Law enforcement:** Biometric authentication ATMs, entry control, law enforcement, airports and government programs.
- **Internet Banking:** Biometrics have an application that it can be used for increasing the security of internet banking. The contract between a bank and an application service provide can need biometrics based verification for a high value transaction over the internet.
- **Commercial applications:** By employing biometric solutions, a higher level of trust is provided by businesses to valuable information and applications on networks and webpages. The authentication of users will be done using biometrics and they are allowed to access the desire data

and applications and the conduction of business will be done in a secure manner. Those customers who have very sensitive information like working in healthcare industries, financial services and markets of government, can have greater security levels when permitting workers, partners, and access to business critical information and applications.

- **Healthcare:** Provide security and convenience in large scale and remote health monitoring deployments, timely and accurate diagnosis and privacy of health related documents etc.

- **Time and attendance system:** Offers useful savings of cost or increasing return on investment (ROI) in areas like prevention loss or time and attendance for ensuring the efficiency of workable environment.

2.3 Growth of Biometric Industry

The rising research and development in the field of biometrics is a making a potential industrial market and increasing the economy in a great revolutionary manner. The higher threats of security are deriving demands of biometric industry in the future expects the deploying of these biometric systems at high rates. In figure 2.1, the revenue generated by biometric industry of the United States in previous and current years that shows the importance of these systems and acceptance both industrially and commercially. But, challenges are greater in the initial deployment costs of biometric systems that hesitate the investors from investing in this industry.

2.4 Comparison of Biometrics with Traditional Methods

There are two methods of traditional methods in identification process adopted by researchers; the first method is based on knowledge and the second one is called token based method. In the knowledge based techniques the users apply their passwords and personal identifications (PIN) whereas in the second methods that is token based they apply other information such as physical keys, ID cards, and chip cards. In contrast to traditional methods, inherent information of users is used in biometric system that is very simple, highly reliable, convenient, easy to use, and more secure for the procedure of identification.

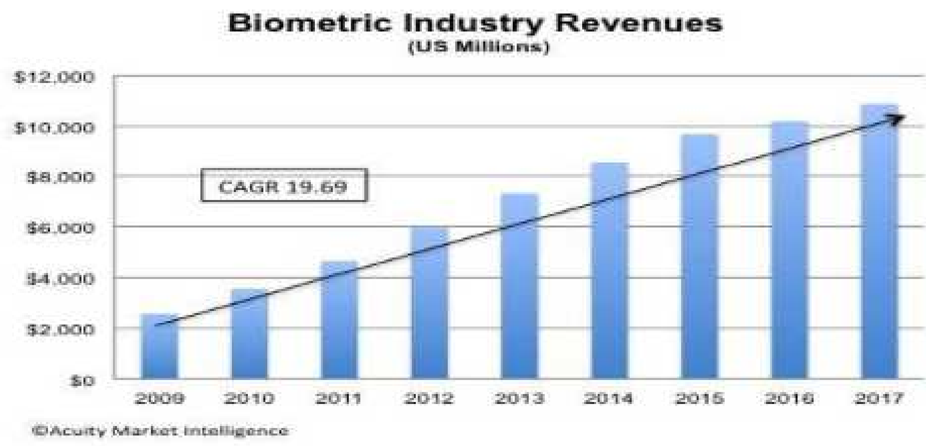

Figure 2.1: Revenues generated by biometric industry in the United States

Now a day, biometric systems are employed in recognition systems that are extensively utilized in environments of high security and they replaced traditional systems that are knowledge and token based approaches and are highly sophisticated, accessed, and controlled by electronic devices. The purpose of deploying biometric systems is that the methods based on traditional approaches have some drawbacks such as copying, forgetting, stealing, losing and sharing. It is very easy to crack the weak passwords by hackers whereas strong and complex passwords are very difficult to hack and remember. Because of inherit properties of users utilization in biometrics, a superior solution is provided that lacks in the traditional identification methods and lot of work and effort is needed for forging, stealing, and falsifying the users identity. Also, it is difficult to forget and lose biometric information of a user. Finally, the use of biometrics provides greater convenience to the user and a single system is able to replace multiple passwords, security keys, and identification IDs.
There are some challenges also faced in deploying biometric systems for identification process and these will be discussed later in the Chapter. Several standards are applied on biometric systems that are controlled by regulatory authorities. The most famous among these regulatory authorities is ISO/IEC JTC1/SC37 for measuring the scalability and performance of biometric systems that interpret information utilizing personal technologies for identification.

2.5 Challenges in Surveillance, Security and Privacy

Due to diversity found in critical civil applications such as crossing the international border, safe and remote transaction of money, and demands of criminal inspection a stringent level of security is required that the traditional methods of identification were failed to fulfill these demands. This increasing demand of full proof security necessitate the requirement of more reliable identification source that would mostly rely on the intrinsic properties of person instead of extrinsic properties such as keys, IDs, etc.
To counter the challenges like security, privacy protection, control of access, identification management of access, and identification of individuals in groups and subgroups under surveillance, biometrics in computer science are studied for countering such challenges. Some of the applications of biometrics in surveillance are; user continuous recognition, wearable and unobtrusive instruments for authenticity, applications in government and forensics industries, surveillance in banking and finance fields, surveillance in IP and digital technology, applications in military, copy write protection in multimedia, and record of medical management.
Additionally, biometric modalities are able to cope the challenges faced in the fields of falsification and forgery. Some of the challenges are; threats of circumvention, replay attacks, falsification of IDs, and complication of biometric systems.

2.6 Biometrics Classification

The foundation of modalities for biometrics are categorized into two distinctive clusters; the first one is named as physiological traits and the second one is called behavioral traits. Those biometric systems for identification that are comprised of shape of body or individual anatomy fall into to the category of physiological traits. Some of the examples are: fingerprints, iris of eye, shape of face, pattern of ear, geometry of hands, shape of retina, structure of DNA, ECG, EMG and EEG. Similarly, some of the examples of behavioral traits are: pattern of speech, gait, individual signature, and rhythms of keystroke. The classification of biometric identification systems is shown in figure 3.
There is less effort and hardware required in acquiring behavioral signals through systems based on behavioral traits. Time variation and situation occur in human behavioral properties. The challenges faced in behavioral

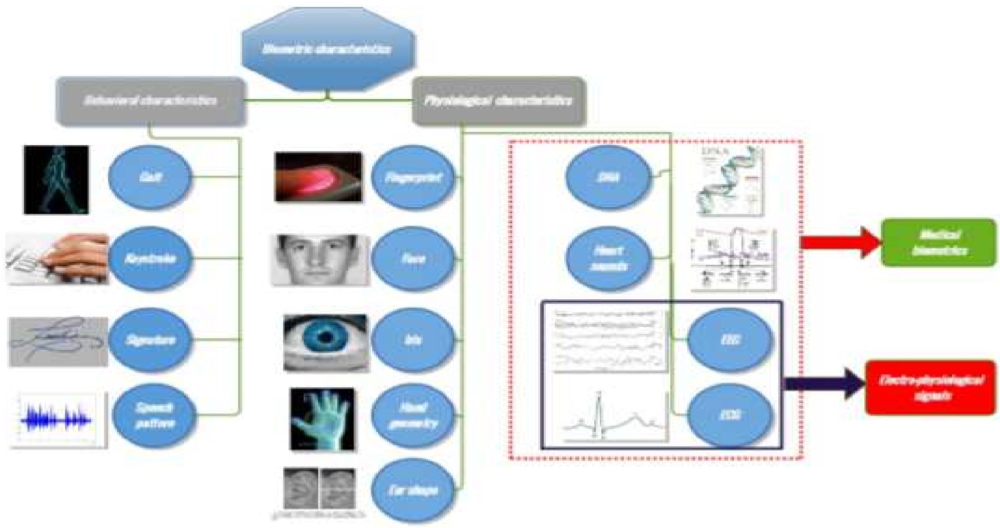

Figure 2.2: Biometrics Classification

attributes are: variations in time, permanence of lower degree, less performance, lower unique properties, and continuous acquisition of data. These systems also offer some benefits such as unobtrusive acquisition of data, easy acquiring of data, lower cost, independent of user permission, lower hardware, and more eïňĂective and remote data acquisition procedure.
Similarly, there is time invariance found in physiological attributes. Some of the challenges and issues faced in these attributes include: less effective procedure of data acquisition, requirement of efficient hardware, and dependent on user permission. They also offer some benefits such as permanence of higher degree, greater performance, instantaneous and without delay acquisition of data, highly unique, and time invariance. The comparison of physiological and behavioral traits is shown in table 1.

2.7 Criteria of Evaluation

2.7.1 Authentication, Authorization and Identification

The evaluation criteria of biometric systems depend on few terminologies that are necessary to be defined from mixing and basic understanding.

- The first term used in evaluating biometric system is its authentication

	Behavioral Traits	Physiological Traits
Permanence	Low Degree	High Degree
Performance	Low	High
H/W Required	Less Specific	More Specific
Remote Access Data	More Effective	Less Effective
Uniqueness	Less Unique	More Unique
Data Acquisition	Continuous	Instantaneous
Time Dependency	Time Variant	Time Invariant Mostly
Collectability	Unobtrusively, Easy	Require User Permission

Table 2.1: Comparison of physiological and behavioral traits

that is utilize for verifying a user actuality. The implementation of authentication is very easy and based on one to one matching.

- The second term is authorization that shows the user permission towards accessing something. Positive authenticating of a user results into his authorization.
- The third term is identification and it distinguishes a user among groups and subgroups of individuals. This process is difficult to implement and based on one to many matching.

Identification is the most difficult problem than authentication in biometric systems of identification. The reason is it requires 1: N matching where N represents number of individuals in a group but authentication is based on 1: 1 matching. Due to multiclass classification problem, the process of identification requires an efficient and complex computation.

2.7.2 Performance

- The first step in measuring the performance of a biometric system is its accuracy that is defined as the percentage of correct classification of instances. Accuracy can also be calculated by adding true positive (TP) and true negative (TN) divided by total number of samples and is given in equation 1. But, accuracy is unable to give the complete evaluation of performance due to non-sensitivity towards distribution of class.

$$Accuracy = TruePositive + TrueNegative/TotalNumberofSamples \tag{2.1}$$

- The second important parameter to evaluate biometric system performance is receiver operating characteristics (ROC) curve and is considered the most general criteria of evaluation for classifying performance.
- Confusion matrix also play an important role in evaluating performance and is able to show several aspects such as true positive, false negative, false negative, and false positive.
- The statistics made by Kappa also evaluate the performance of a biometric system. If the value of Kappa is higher than 0 then it shows better behavior of system as a classifier rather than chance.

2.7.3 Errors

Type-I and Type-II are two types of errors found in biometric matching.

- The Type-I error is called false rejection rate (FRR) or false non-match rate (FNMR) and it shows the rate of failure of authorized individual during the process of identification [11].
- The Type-II error is called false acceptance rate (FAR) or false match rate (FMR) and it shows the rate of incorrect identification of authorized individual [11].

If biometric system is used for validation process, FAR is applied to measure system security whereas FRR is applied to show the level of its inconvenience. The usability of biometric based identification system is highly effected by these errors in applications like civil applications that require equal values of FMR and FNMR whereas in high security applications the values of FMR and FNMR are kept lower. Similarly, lower values of FNMR and FMR are also applied in forensics based applications. Type-I and Type-II errors in biometric systems are shown in figure 2.3.

2.8 Biometrics Selection Criteria

Because of not having a single method applied in biometric identification process and also every biological attribute is not good enough on the bases of which the biometric systems for recognition process are deployed. The criteria that qualifies any biological trait for biometric recognition system is discussed under:

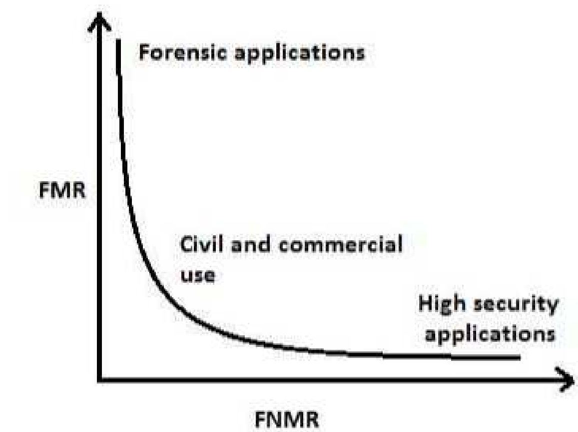

Figure 2.3: Error rates and their effects on several applications of biometrics

- The first criterion of biometric system selection is its universality that defines the general possession and trait availability in all individuals. In case of non-universality such as disability of a person, he is not allowed to register his trait in cases of gait, fingerprinting etc. and results into an error called finger to enroll (FTE) error.

- The second criterion should be its uniqueness that is defined as acceptable distinction of trait in persons such as two individuals should not have identical and duplicate characteristics. If strong variation is absent, then will result to a higher FAR in this situation

- Permanence is also important criterion in selecting a biometric system because the characteristics of an individual should be permanent and should not vary with time. If there is less permanence, a higher FRR will be observed.

- A biometric system should have a higher accessibility that means process of data acquisition should be convenient and have intrusive nature. The processing of raw data should be easy and failure to acquire (FTA) error will be observed in case of accessibility inconvenience.

- The system should be robust and highly resistant to spoofing attacks and forgery.

- The system should be acceptable to user and he should not face any reluctance while using this system.
- The performance of system should be better enough that its accuracy is not effected by errors and its cost is lower and highly efficient in computation.
- The system should be able to detect liveliness of a user and it should verify the genuine biometric patterns of an individual such as temperature, pulse etc. The liveliness detection might be based on both software and hardware approaches.
- The system should have the ability to monitor continuously individuals that are already monitored.

2.9 Summary

The introduction of some biometric systems, their classification along with importance are presented in this chapter. The comparison of traditional identification techniques with biometric systems are also discussed and explained with applications utilized in modern world. To give an enlightenment of ECG based identifications and goodness, both evaluation and selection criteria are discussed in the chapter. The terminologies used in this chapter will be helpful in understanding rest of the chapters of this thesis.

Chapter 3

Electrocardiography (ECG)

3.1 Introduction

Heart generates an electrical activity that is recorded on the surface of body by means of electrodes. This recording of electrical activity is called electrocardiography (ECG) [12]. Waller observed for the first time ECG and he used his pet dog as a source of signal and capillary electrometer was used for its recording [13]. The technology was further improved by Einthoven in 1903 after the employment of string galvanometer for recording purpose and human subjects with variety of cardiac abnormalities were used as sources of signal [14]. The concept of labeling of various ways, definitions of some standard recording sites on arms and legs, and the development of first model of time varying dipole were introduced by Einthoven and these concepts are still applicable in modern world [12].
For recording ECG, there are two points on the body are made in order to achieve differential recording. Usually, each differential is recording is called lead. Three lead numbers are defined by Einthoven and these are represented by Roman numerals I, II, and III. These are shown as under:

$$I = V_{LA} - V_{RA} \tag{3.1}$$

$$II = V_{LL} - V_{RA} \tag{3.2}$$

$$III = V_{LL} - V_{LA} \tag{3.3}$$

Where, LA is the abbreviation for left arm, RA for right arm, and LL is for left leg. Due to the assumption of resistive nature of body for at ECG frequencies, the wires are assumed to be four limbs attached with torso. Therefore, the recording of lead I is perfectly done without any loss of cardiac information from the shoulders. The relationship between the three leads is shown below:

$$LeadII = LeadI + LeadIII \tag{3.4}$$

The concept of unipolar recording of ECG was presented by Wilson in 1934 [15]. A reference point was created by tying the three limbs and average potential was found for recording the individual sites of recording on limbs or chest surface to get the differential recording from the same point of reference. The biophysical models were extended by Wilson for including the cardiac source concepts enclosed within the body conductor volume. The central terminal was regarded as at true zero potential. Therefore, from 1930 to today, out of total 12 leads, there are 3 limb leads, 3 leads are meant for modified reference potential, 6 leads are placed on the chest front and are the reference leads with the Wilson terminal and form the foundation of 12 lead ECG recording. The whole phenomenon is shown in Figure 5. These are the historically based sites having a built-in redundant capacity, and are considered non-optimal for all the activities of heart. The ECG is recorded from the voltage difference of any two sites, and these sites are considered the best sites for data collection after observation of 90 years. The recording of a typical ECG is shown in Figure 6 that shows the recording of lead II. Alphabets from P to U were chosen by Einthoven for differentiating them from other alphabets defined for other physiological signals studied in the past. The typical range of ECG lies within Âś2mV the recording bandwidth is from 0.05 to 150 Hz. American Heart Association [16] and Association for the Advancement of Medical Instrumentation [17] proposed full technical specifications of ECG instrument.

Several attempts have been made to change the approach of recording the ECG signal. A weighted set of recording sites are used in vectro-cardiogram in order to form a lead set of orthogonal xyz plane. The best advantage of this approach is that it requires minimum lead set but moderate physicians use this approach. There is need of many recording sites in body surface mapping that are arranged on the body so that surfaces at same potential can be easily computed and they are analyzed efficiently. There is great role of this approach in the field of research. Beside the 12-lead ECG, other subsets of it are being used in limited recording mode like the tape recording ambulatory ECG have 2 leads, recording for intensive care monitoring at bedside have 1 or 2 leads, and telemetry of patients in hospitals that are not confined to their beds contains usually 1 lead for recording. The modern

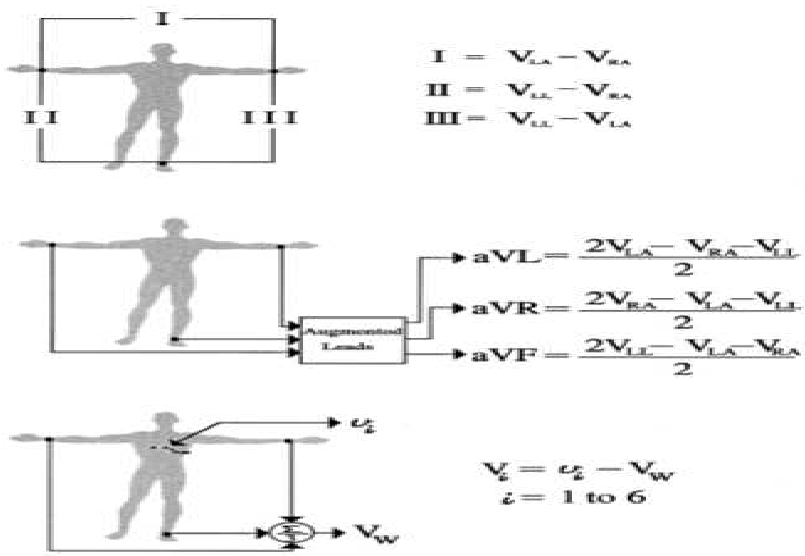

Figure 3.1: Scheme of 12-lead ECG

ECG machine has the following components such as vacuum tubes, microprocessors, integrated chips, and transistors.
The use of computers in medicines for interpreting the ECG signal is one of the applications of computers [18]. The use of computers was basically to eradicate the human observation and improvement in the ECG recordings. Initially, telephone lines were used to interface the ECG machine with centralized computer. The components of modern ECG machine have an analog front end, a 12 to 16 bit A/D converter, microprocessor for computation, and dedicated input-output processors. A matrix was obtained from the 12-lead signals and that matrix was then interpreted by using several algorithms for data processing [19]. The ECG heartbeat along with types of heart beats are shown in Figure 3.3. The signals obtained from 12 leads and its depiction is shown in Figure 3.4.
These correct and inappropriate signals will be read by the physician and also will give his comments and prescription to the patient.
Several interpretation statements can be made to diagnose ECG but the use of ECG is possible only for five to six group of ECGs. The first and important step in the analysis of ECG is the rate or rhythm made by the contraction of atria and ventricles. There might be conduction disturbances within the chambers or disturbances between the chambers. After that the

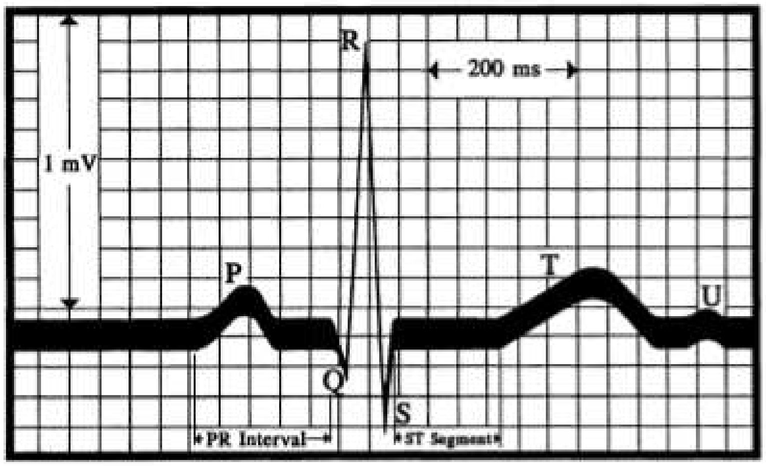

Figure 3.2: Typical ECG signal Recorded with Lead II

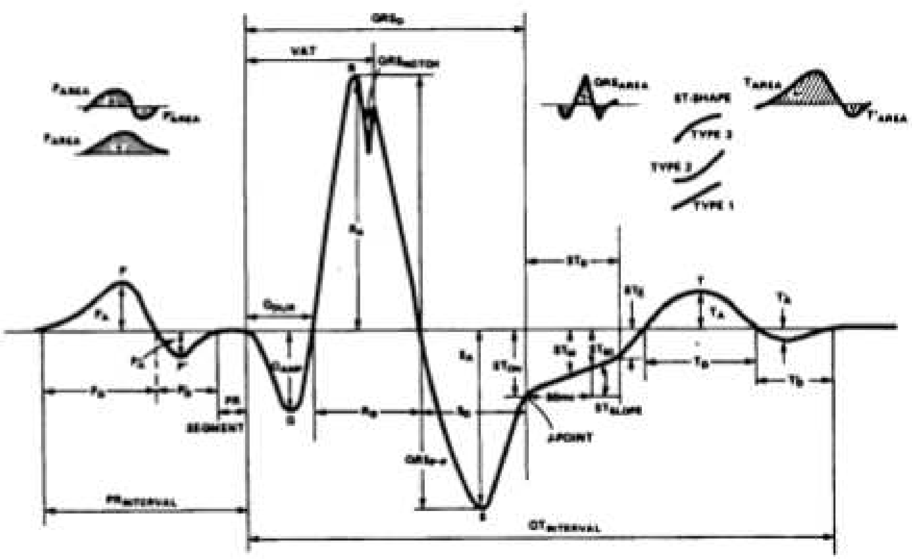

Figure 3.3: Computer Algorithms for depicting the ECG signal

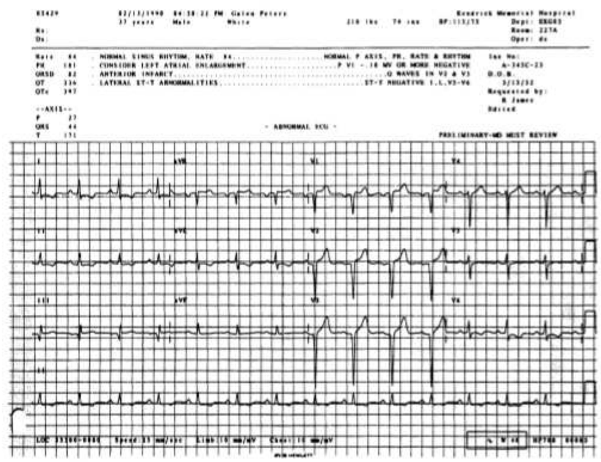

Figure 3.4: Interpretation of 12 lead analog signals I

infraction of myocardium scarring is identified to result in the feature extraction. Also, beside these factors acute events might be present such as in the case of Ischemia or infarction of myocardium. To find the size of chamber or its enlargement, ECG can be used as a primary tool, but, noninvasive image technologies might produce better results. Additionally, the development of high resolution ECG is achieved and the digitized ECG is the average signal for random noise reduction [20]. Later on the technique of post averaging was used so that high pass filtering is applied to detect the low voltage signal of about 1 micro-volt that is undetectable by other standard methods. This technique of recording is very efficient for predicting the life threatening events of a patient heart [21].

3.2 Physiology of ECG Activity

There are four chambers of heart; the upper two chambers are called the atria and the lower two chambers are known as ventricles. The walls of atria are thin, with low blood pumping capacity and have the ability to receive blood from the venous circulation. Group of cells are located in the top of right atrium that are regarded as the heart pacemaker. This pacemaker is called the SA-node. Due to the ionic concentration changes across the cell membrane, a voltage potential is developed that excites the cells near to the cell membrane, and the propagation of cell to cell electrical current is achieved. Due to the resistive nature of body this electrical activity is passed to the whole surface of the body [22]. The characteristics of the surface of body are dependent on the amount of tissue activation at a time and the direction and speed of the activation wave fronts. Hence, the potential of pacemaker generated by small group of cells cannot be seen on electrocardiogram. Because, there is an increased atrial muscle activation, the start of ECG activity is seen on the surface of body and therefore results in the observation of first ECG signal of cardiac cycle. This initiative wave of ECG is called the P wave and it shows the atria activation. This ECG activation proceeds through a special group of cells known as the AV-node and His- Purkinje system that are again very smaller structures for generating a single enough larger to be seen on the standard electrocardiogram. Again, a short, isoelectric segment is observed that follows the P wave. There is a large deflection observed after the excitation of large ventricular muscles. This ventricular excitation of muscles allows the ventricles to contract and pump the blood from heart to other body organs. Several components are seen in this large wave. Q wave is the initial downward deflection, R wave the initial upward deflection, and the terminal downward deflection is known as the S wave. The polarity of these components is dependent on position of leads attached on the body and different kinds of abnormalities that might be seen. This larger ventricular waveform is generally known as the QRS complex. There is another short isoelectric segment that follows the QRS complex. After this, the ventricles relax and a small wave of low frequency is seen that is known as T wave. Also, along with âĂŸTâĂŹ wave there is another segment of wave seen in some individuals that is called the U wave. The origin of this wave is not known but it might be due to the repolarization activity. The anatomy of human conduction system is shown in Figure 3.5.

3.3 ECG Instrumentation

Professional societies addressed the ECG instrumentation general requirements for many years. Shortly, the bandwidth of system is recommended by them is from 0.05 to 150 Hz. There is greater significance of lower frequency response of the system due to regions of lower frequencies such as ST segment that have critical value of diagnosis. As the heart rate has a fundamental frequency of 1 Hz, the high pass analog filters phase responses are of such nature that the corner frequency of system should be less than 3 dB that is why the amplitude response of the filters should be in consideration. The system design only decides its gain. The amplitude of ECG signal is about Âś2mV, and if analog to digital conversion is used, there should be an

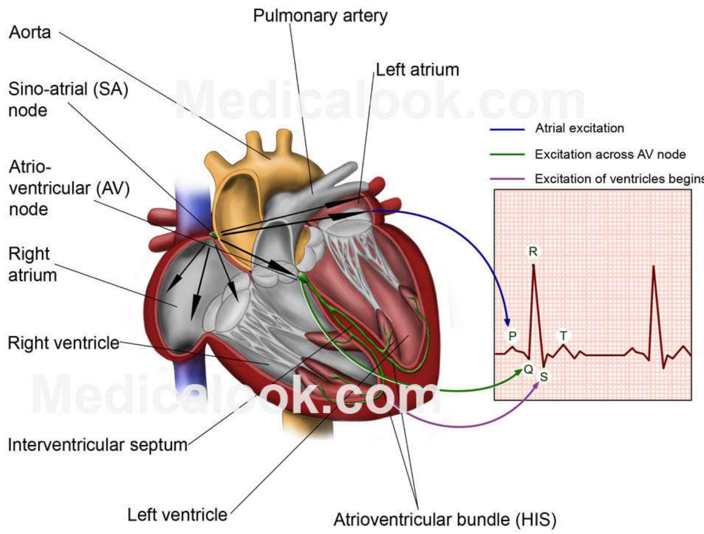

Figure 3.5: Anatomy of Human Conduction System

appropriate gain for spanning the full range of analog to digital converter.
The first important thing in getting an ECG signal is the connection of patient with the front end of amplifier. A bio-electrode is used for converting the patient ionic current into metallic wire flow of electrons. The dependence of electrodes is mainly on the chemical paste or gel that have a high concentration of ions. This gel works as a transducer between tissue and electrode interface. For short time duration and use, silver coated suction electrodes or sticky metallic foil electrodes might be used for signal detection. Whereas, in long term duration and proper monitoring of patient, tissue-electrode interface of highly stable electrodes is needed with adhesive tape material that surrounds the gel and Ag/ AgCl electrode.
The patient might be connected to several devices at any particular time such as BP monitor, respirator, artificial pacemaker etc. that invade the surface of body and provide a pathway of lower resistance to the heart. There should be taken some precautions such that the device should not act like a current source that injects current and results in the stimulation of heart muscles and cause fibrillation in heart. There are some unavoidable currents at the input stage of the system, and the leakage value of these currents must be lower than 10 micro Ampere/device. This is the readings in normal situations, but in the conditions during which the patient is in contact with the

main alternating high voltage lines, the leakage currents of 10 ÂţA must be protected. This shows that the reference ground of the ECG should not be physically connected with the lower side of the AC supply lines. The best solution of solving this problem in ECG machine is that the ECG signal should be modulated with a frequency of medium up to 400 kHz and there should be an isolation transformer with consequent demodulating capability. Other techniques of isolation might be taken into account, but aim of the above discussed method is to protect the patient from connection with power AC lines in order to recover the patient to power line fault. In some cases, a ground buss of lower impedance is also installed in the rooms to remove the potential hazards and each of the device is connected with a ground wire of the buss. Additional features of these amplifying devices include their ability to withstand huge discharge of cardiac defibrillator energy.

The ECG machines used in the past contained one lead recording at a time that later on evolved to three leads recordings. This required the utilization of switching as well as other analog weighted circuits for generating the various 12 leads. The digital systems of today do not have such type of bulky combination of circuitry instead they have an individual amplifying circuit for each electrode on the surface of the body. There is A/D conversion of each electrode signal and the mathematical implementation of all the leads is done in the software. This would require a system of 9 amplifiers. By doing some mathematical calculation after the application of differential amplifier, the system can be reduced 8 channels. The modern digital ECG system is shown in Figure 3.6. The modern digital system has the following components; it contains 13 single ended amplifiers, and there is an A/D converter that has a resolution of 16 bits that are enfolded in an amplifier stage. Also, there is an isolation of digital signals and they are sent through a high speed optical link to the main system of ECG machine. Additionally, a CPU and DSP processers are installed in the system with resolution of 32 bit that performs all the calculations and result into the generation of a hard copy. This is shown in Figure No.4. The important feature of digital ECG machine is to be noticed that all the functional blocks have their own controllers and a real time multitasking operation system is required for coordinating all the functionalities of the system. The data acquisition and data interpretation programs are highly sophisticated and are evolved continuously but still this is the main legal requirement that physicians over read these ECGs.

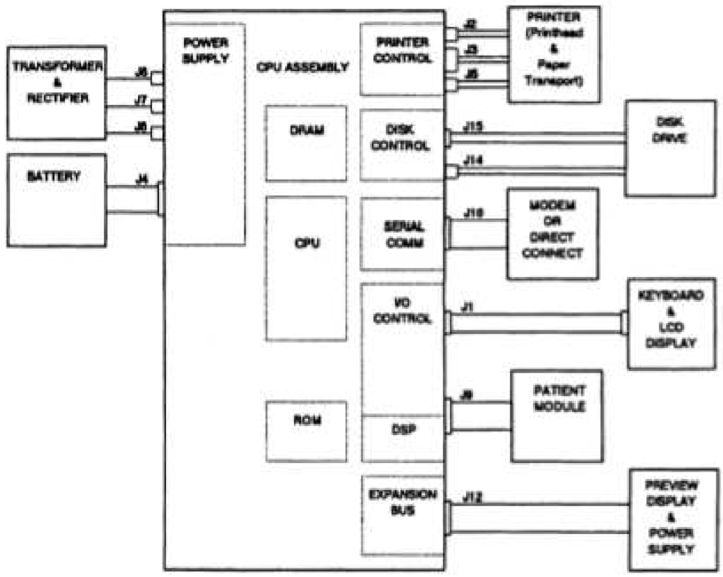

Figure 3.6: Block Diagram of Modern Digital ECG System

3.4 Applications of ECG

The applications of ECG are discussed as under:

3.4.1 The Ambulatory ECG

This ECG is called the Holter ECG and was discovered in 1960 by Dr.Holter [23]. The important use of this type of ECG was for the identification transient heart blockages in patients who were already implanted with artificial pacemakers. This need the development of a secondary device that was able to able to play back the 24 hours of tape recordings of ECG in order to show the physician in situations where patients had an abnormally lower heart rate. There were scanners that had the ability to play the tape recordings of ECG from 30 to 60 times in real time along with the detection of heart beats and to show them on the CRT screen. Additionally, for the identification heart beats, an audible tachometer was used for this purpose. There were numerous other observations came up with this play back ability such as the premature ventricular complexes identification that result in the development of methods for identifying and quantifying their number. There was a relationship achieved between the diagnostic tool and pharmaceutical therapy in order to quantify the premature ventricular complexes. The recording of tape ECG was done before the administration of drugs, and the efficacy of drug was measured after the reduction in number of premature ventricular complexes. Arrhythmias were quantified and detected by using scanner technology and the implementation was done by using analog circuitry and later on became very feasible after the digital techniques of interpretation. The use of sophisticated algorithms and pattern recognition techniques lead to the tape back up to more than 100 times in real time. Unluckily, the approach is declined to identify and treat the arrhythmias of heart due to rationale of pulmonary ventricular complexes suppression that is unsuccessful for the improvement of heart mortality [24]. Although, the use of ambulatory ECG is still a diagnostic tool, and the modern machines have built-in microprocessor units with huge RAM and small disk types of capacity larger than 400 MBs. The online analysis of data can be done by selecting larger segments of data to store and analyze it on personal computers for later on usage.

3.4.2 Monitoring of Patient

The real time ECG monitoring techniques were developed for coronary care unit (CCU). These specialized hospital units had patients for their careful observations and to analyze their progress in acute illness like infarctions of myocardium or after complex surgery. Due to increase in beds in these specialized caring units, it was difficult for doctors to monitor all the patients and therefore, the need of computer monitoring systems became famous for monitoring the patient circadian rhythms. The programs installed in these computer systems were not specialized as were installed in ambulatory ECG machines. There were about 8 to 16 beds in a typical CCU, and the power of computation was limited by multiple beds monitoring. The systems present today have distributed CPU within the module of ECG at the bedside along with other physiological monitoring modules. There is an interconnection of each monitor with a high speed efficient digital line. For example, connection of Ethernet with a centralized computer for controlling communication and maintaining the database of patients [12].

3.4.3 ECG with High Resolution

The capability of high resolution is now becoming the standard most modern digital ECG machines or a unit of standalone microprocessor. The important application of high resolution ECG is the recording of very low voltage signals with amplitude of 1ÂţV that happen after the QRS complex but have no evidence in standard ECG signals. The generation of such type of late potentials is actually from the abnormal ventricular regions and are responsible for increased pulse rate that is the biggest threat for life. A configuration of 3 bipolar leads is used in the form of anatomic xyz coordinate system in high resolution ECG machines. The digitization of these 3 ECG signals is done at a sampling rate of 1 to 2 kHz and are timely aligned with the help of QRS correlator after summing them in the form of signal average. Averaging of signals is utilized for improving signal to noise ratio by taking square root of the average number of heart beats. The assumption made in this process is that there is no variation in the beats and the noise in the signals is probably random. The most common sequence of late potentials in high resolution ECG processing uses four panels and is shown in Figure 11. The first panel shows a recording of the xyz leads that is much closed to normal resolution for 3 seconds. In the second panel the sampling frequency is kept 10 times more than the first panel and shows averaging of 200 beats. Also, this signal is 5 times more amplified than the first one. The signal shown in the third panel is a filtered signal with a high pass filter that is a partially time reversed digital filter with a response like a second order Butterworth filter with a 3 dB 40 Hz corner frequency. Similarly, the signal in fourth panel derives several parameters such as total duration of QRS complex, terminal root mean square voltage at 40 milliseconds, and signal of low amplitude starting from 40 ÂţV to the late potentials end. Based on these parameters, abnormal values are helpful in identifying the high risk of ventricular tachycardia in patients that later on result into angina pectoris and heart attack [25].

3.5 ECG Noises and Their Origin

There are some noises that exit in ECG signal recording and their origin is discussed below:

3.5.1 Baseline Wander

When subject moves during the process of acquisition, impedance changes occur in the body electrodes that produce low frequency distortion in the ECG signal. Additionally, respiration, unbalanced placement of electrodes, and electrodes misplacement can also result in these low frequency distortions. These low frequency distortions in ECG signal is known as baseline wandering or baseline drift. The deviation in the amplitude of the signal

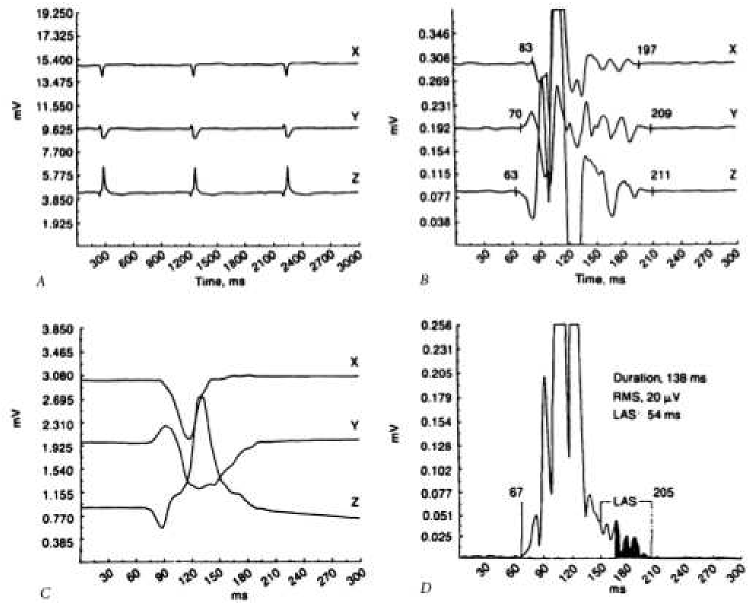

Figure 3.7: Signal Processing steps in high resolution ECG

due to baseline wandering creates difficulties in detecting the R peak and additional signal processing [26].

3.5.2 Interference of Power-lines

External sources such as nearby devices and inappropriate grounding of electrodes produce high frequency components that causes ECG signal corruption. Such type of distortion in the signal put challenges in the signal processing process and automated diagnosis of data uniqueness. A low pass filter of 50 Hz can be used for removing this noise because most of the components of noise are in the frequency range of 50 t0 60 Hz [26].

3.6 Biometric Properties of ECG

3.6.1 ECG Uniqueness

- The first unique property of ECG is its liveness detection because its presence shows the liveness of a patient. This property reduces the liabilities of fooling attacks deprived of approval of patient.

- The second important feature of ECG is its unique feature because every person has a unique cardiac rhythm even for identical twins. Several problems in other biometrics occur for identical twins such as biometrics based on iris and face detection.
- ECG is very robust and has resilience in circumvention.
- Other biometric systems degraded with time due to changes in finger prints, age factors, physical health conditions, facial features modification, and iris changes with time etc. but ECG shows a high permanence and has very less chances of changes with time.
- One of the unique feature of ECG is its template size because it is one dimensional signal as compared to other two dimensional features such as face, iris etc. If it is divided into small fragments, it provides a template of low size that assists in the decrease of computational cost and complexity as well as time of computation. This lower template size of ECG signal needs less space for storage and is very portable.
- ECG is very universal and everybody obeys this property of universality. There are some drawbacks in other biometrics and are unable to enroll data in certain conditions such as iris in blind persons, fingerprints in amputees, voice in deaf, and gait in the paraplegic cases. Such drawbacks limit other biometrics universality.

3.7 ECG Comparison with Other Biometrics

Some trade-offs are observed among different biometric modalities in terms of several features such as permanence, uniqueness, universality, accuracy, collectability, user acceptance, robustness, complexity, and cost. A comparison of ECG based biometric identification with several widely used in today world is shown in Table 3.1. The main objective of biometrics research includes robustness of system against the problem of circumvention in which performance cannot be compromised. Several vulnerabilities are found in different biometrics against the problem of circumvention and replaying of attacks are made regardless of the approaches used in their implementation. Some of the examples include the iris circumvention in which duplicate lenses are used, latent prints are made from fake fingers, features of face and its masking, and mimicry of voice. In these type of attacks either cooperation of subject is required or sometimes not. But these circumventions and replaying attacks are protected in ECG based identification systems due to its

	ECG	Finger Print	Iris	Face	Voice	DNA
Permanence	H	H	H	M	L	H
Uniqueness	H	H	H	L	L	H
Universality	H	M	H	H	M	H
Accuracy	H	H	H	L	L	H
Collectability	M	M	M	H	H	L
User Acceptance	M	M	L	H	M	L
Robust to Fraud	H	M	L	L	L	H
Complexity and Cost	L	M	H	M	L	H

Table 3.1: Comparison of ECG with other Biometrics

robustness. Additionally, ECG also provides high uniqueness, universality, and permanence. Like in face recognition based biometrics, there is chance of high non-match error rate, unreliability in the problem of identical twins, and vulnerability exits in various conditions and emotional behaviors. Due to intrusive nature of acquisition and smaller circumvention resilience, iris recognition is accepted by users up to a very smaller extent. Also, noise problems in voice and because of variable nature, it has very lower accuracy and less followed in biometrics. Forensic applications use DNA recognition but due to its intrusive nature it is also less accepted. Because of problems like sensor conditions, skin aging effects, and less capability of data enrolling in few conditions, finger print technology is also affected.

3.8 ECG Biometrics Open Research Challenges

ECG based biometrics include some emerging challenges, and these are discussed below.

- The first challenge in ECG biometrics is security. Due to robust nature of ECG, it is the most acceptable option but if it is attacked by someone can produce lasting effects on this type biometric technology. Therefore, the transmission of ECG over internet should be protected by utilizing some techniques of encryption such as Advanced Encryption Standard (AES) and it can also be secured by wavelet feature extraction and modification techniques [27].

- The second challenge is ECG acquisition time. As ECG is non stationary and infinite signal, its acquisition for longer duration of time can produce delays in processing that ultimately increase the cost of computation and complexity. There, it is needed to have a reliable system based on smaller size of signal in order to avoid the delays in its processing.

- The third challenge in ECG biometrics research is the population size. Due to larger population size, there is chance of multi-class problem of classification that ultimately results in decreasing the performance of system. In large scale deployment of ECG biometric system and its commercial and viability, this is the most prominent factor that limits feasibility of this technology. Performance is also reduced due to unbalanced and uneven distribution of data among different subjects.

- The fourth challenge faced by researchers in deploying this technology is cardiac anomalies. Similar arrhythmias for same subjects have no effect in cardiac disorders but unusual shapes of arrhythmias create difficulties in feature extraction and detection of various peaks. One of the major causes of increment in heart rate variability (HRV) is arrhythmia [28].

3.9 Variability in Heart Rate

Morphological changes in ECG are not static and they are depended on several factors. Fluctuations in heart rate or RR interval over time result in HRV that might be due to some physical exercise or occurred due to some state of emotion. Several time related features can be determined by these variations. But some problems also occur such as intra-subject variability augmentation that leads to the decline of overall system performance.

3.10 Arrhythmia

Any abnormal rhythm of heart that can cause normal cardiac cycle distortion is called arrhythmia. Such type of abnormal behaviors is because of improper hear muscles functioning such a premature contraction of atria and ventricles, and fibrillation of atria and ventricles. Sinus arrhythmia is the result of cyclic variations in hear rate because of breathing. Computational complexity of a biometric system increases in the presence of arrhythmia.

3.11 Summary

This chapter covered a brief overview of electrocardiography, historical background, anatomy and physiology of heart working for generating ECG signal, ECG instrumentation, and some applications of ECG. From the discussion, it is also observed that ECG is very important in predicting the cardiac conditions of a patient. Additionally, this chapter covered some important aspects of ECG biometric systems and overviewed the emerging challenges faced by researchers in deploying this technology commercially and industrially.

Chapter 4

Literature Review

4.1 Techniques of Signal Processing

In 2005, Israel and his fellows worked on proper step of filtering to remove noise from ECG signal A bandpass filter with corner frequencies range of 1 to 40 Hz was used by the rejection of noise related spectral components [29]. In 2002, Shen and his coworkers worked on removing base line wander, noise from power line, Dc offset components, and interference of high frequency after preprocessing on ECG signals [30]. Zhao et al. removed the effects of heart rate variability after normalizing the heartbeat [31].

4.2 Feature Extraction Approaches

There are different approaches used by researchers for ECG based biometric recognition and these approaches can be divided into approach based on fiducial detection, approach based on signal processing (such as DWT, EKF etc.) and other approaches (such as statistical, Legendre polynomial etc.) with having both advantages and disadvantages. Detection of fiducial point involves complex computation because ECG signal has high variability and this approach loses some important information hidden behind the pattern of ECG complete morphology. But, in non-fiducial approaches, there is computation only on the useful dataset and irrelevant information is discarded due to inter subject variability enhancement and reduce the intra subject variability at the same time.

4.2.1 Approach of Fiducial Detection

Due to complex structure of ECG, it is a time varying repetitive signal that contains both local maxima and minima. Every heartbeat contains these peaks and these are the landmarks of ECG signals. The classification of these landmarks are called fiducial points and these are P, Q, R, S, and T waves. The first ECG based identification algorithm using approach of fiducial detection was proposed by Biel et el. In 2001. They utilized SIEMEN ECG instrument that was able to detect a set of 30 clinical diagnostic features directly. P. T, and QRS complex were present in the feature set that was composed of their amplitude and duration. They used only 3 out of 12 recording leads in static position of hand and the reduction of features was limited to only 12 features after the removal of features with high correlation by using a matrix of correlation. The classification of features was done by using self-independent modeling of class analogy known as SIMCA. The variance among dataset was estimated by PCA score. 20 subjects were taken with age range between 20 to 55 years for testing and their accuracy was reported up to 95 percent. This study was very important because it revealed the cardiac signals importance for the purpose of identification with a high acceptable rate of recognition. But, there was no automation seen in the process of extraction and selection of features. Specific hardware was required for extracting the features that was restricted to only few medical diagnostic features whereas the selection of features was dependent on the correlation matrix that identified similarity between different features [32].
In 2002, verification of identity based on single lead ECG was done by T.W. Shen et al. by combing two different techniques: the first technique compared the two QRS complexes correlation coefficients by using template matching and to strengthen the decision based on the comparison decision based neural networks (DBNN) were used. MIT/BIH database was used to get QRS complexes and a set of 7 fiducial points were extracted from 20 subjects with an accuracy of 95 percent for template matching, the accuracy of DBNN was up to 80 percent, and the accuracy of both techniques was about 100 percent. The authors suggested that variations in heartrate less affected the QRS complex, but the strategy proposed was not robust to be applied for large data sets and it could only be used for the purpose of verification. The reliance of the strategy was on the QRS complex that can be easily distorted with motion artifacts and the detection of QRS complex needed some computation [33].
In 2011, Shen and his fellows worked again on resting scenario of palm based ECG measurement and they took a dataset of 168 healthy normal subjects.

This time, they used four methods that are template matching, mean square error (MSE), LDA distance classification, and decision based neural networks (DBNN). Prescreening was done by using MSE and DBNN was used for classification of second level with 17 fiducial points for achieving an accuracy of 95 percent. Their work had some limitations and was not robust because it was only for health relax individuals, and the identification was based on static ECG without having HRV [34].

In 2005, ECG based identification using temporal features was proposed by Israel et al. Fiducial points detection was required for detecting these features and a feature vector was used to find the distance between these points. Local maximum and minimum radius of curvature of P and T waves were used for detecting fiducial points and then base positions were found. 15 temporal features of 29 subjects were used after the application of 12 lead private dataset and Wilkes lambda was used for the reduction of features from 15 to 12 with orientation of neck and chest electrodes for achieving an accuracy of about 100 percent. To reduce dimensionality, they used linear discriminant analysis (LDA). The factors effecting the ECG based identification and its accuracy were traced by doing different experiments. Their algorithm was robust for both mental and emotional states and they did proper normalization through their algorithm. Due to sensor placement, the ECG variability was also addressed by them. They tested their work for smaller dataset and orientation of leads was invasive to subjects [29]. The most commonly used five fiducial points are shown in figure 12.

In 2006, a paper was published by Zhang et al. in which they presented their work by using PCA for reducing 14 temporal features commonly used and applied Bayes theorem for classification purpose. They used Bayes theorem in such a way that maximum posterior probabilities were computed while prior probabilities and conditional densities of class were provided. A private dataset composed of 502 people was used for testing of their work and the Mahalanobis distance method was used for getting results. The work is considered with a bigger database in the literature for identification purpose based on ECG. But, a very little information is provided by their work and a 12-lead electrodes were used in experimentation with an orientation of limb and chest that could not be considered less feasible solutions for identification based on ECG [35]. In 2007, fiducial points of QRS complex amplitude values were used to compute a two dimensional heart vector by Wubbeler et al. The accuracy was determined by template matching technique. For testing of algorithm, a private dataset comprised of 74 normal and health subjects was utilized. The orientation of electrodes for limbs was reported after using three of its channels. The purpose of algorithm was mainly for

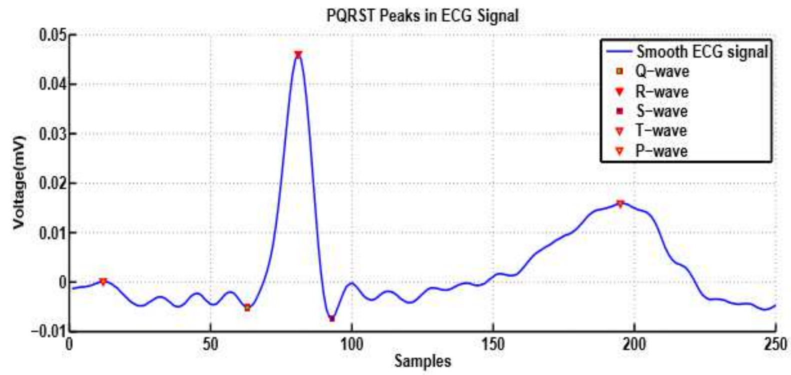

Figure 4.1: Five most common fiducial points in ECG signal

verification and the accuracy was about 98.1 percent with and EER of 2.8 percent along with smaller FAR (0.2 percent) and FRR (2.5 percent). The recording number of ECG varied from individual to individual with a range of 2 to 20 and the sessions of average recording time were about 500 days. Anyhow, their results were limited to only health persons without having HRV and validity was for the purpose of verification [36].

In 2007, fiducial detection technique with an extra feature called feature subspace ensemble (FSE) was used by Silva et al. The selection of features was done by utilization of Sequential Forward Search (SFS). A private dataset of 26 individuals using single lead placement on chest (V2) was used for testing. The classifier in their work was called 1-NN that had a Euclidean distance combined with other sequential classiïňĄers. Each session was based on the individualsâĂŹ cognitive behaviors. The accuracy of the identification was about 99 percent, but with a smaller dataset [37].

In 2013, Silva et al. continued their work and this their approach of something different with a detection based on partial fiducial points. The pattern of heart beat was segmented by computing the peaks of R-wave and then the mean or median of these consecutive patterns heart beat was utilized for forming a template of greater uniqueness. A private dataset of health 63 persons was used in resting state for testing. The collection of ECG signal was from only two fingertips by utilizing a setup of one lead. Cosine distance was used for the removal of outliers because more noise gets into the single from finger tips collection than chest electrodesâĂŹ orientation. The classification of features was done by a classifier called KNN and it had an EER of about 4.5 percent. Resting conditions were limitations of this work it could only be utilized for the purpose of verification [38].

In 2014, the detection of R-peak and segmentation of QRS complex were done by Wang et al. They provided a robust algorithm for irregular conditions of heart. A dataset of MIT-BIH Arrhythmia database comprised of 44 individuals was used for testing. The QRS complex was used for the extraction of templates and multi-functional template matching based on correlation of coefficients was developed for the purpose of identification. The ECG data was collected from two leads and its accuracy was about 100 percent with FAR (11.94 percent) and FRR (0 percent) [39].
Similarly, in 2014, Sidek et al. worked on the equal sampling of QRS complex with a detection approach of R-peak. The classifier used for this purpose was called multilayer perceptron (MLP) and also normalization of QRS complex was achieved by MLP. A dataset of MIT-BIH normal sinus rhythm (NSR) based on 18 individuals was used for identification and the accuracy was reported up to 99 percent. Single lead was used for ECG signal collection and the algorithm was very robust for mobile surroundings. The limitation of their method that dataset was only limited to health persons [40].

4.2.2 Approaches Based on Signal Processing

In 2008, F. AgraïňĄoti et al. worked on second order statistics by utilizing the technique of template matching to get correlation matrix after utilization of normalized autocorrelation that was followed by a transform called discrete cosine transform (DCT) for getting both subject and window recognition rates. The subject recognition rate of their work was about 96.3 percent and window recognition rate was up to 86.3 percent. LDA was performed for getting subject recognition rate of 100 percent and the window recognition of 95.8 percent was achieved. A data set from MIT/BIH normal sinus rhythm (NSR) and PTB databases was utilized for testing and 27 individuals were taken and the technique was independent of ïňĄducial detection. The HRV was also addressed in their work by performing auto-correlation and LDA. This technique was only for the detection of R-peak and ECG signal was obtained from 2-leads [41]. Later on, the method was used with some extension of work for the irregular conditions of heart in 2009 [42].
The technique of AC/DCT with a classifier KNN was adopted by Y. Wang et al. in 2008. They used MIT-BIH (NSR)/PTB database comprised of 13 healthy individuals. The detection of features was independent of fiducial technique and data was collected through 12 leads. The success of identification was with accuracy of about 100 percent [43]. Similarly, in 2013, Raj et al. published their work in which they proposed a method based on auto-

correlation and LDA with removal of outlier for the purpose of verification. A private dataset of 23 persons was computed to get results with ERR of about 4.34 percent. A single arm was used for collection of ECG data with limitations of smaller dataset and restriction of data collection at rest [44]. In 2008, Chan et al. used wavelet transform for segmentation of PQRST by measuring wavelet distance classifier for a dataset of private database composed of 50 individuals and single lead thumbs was used for data collection. This was a feasible work for identification but was based on smaller dataset with an accuracy of about 95 percent [45]. In the same year 2008, Chiu et al. worked also on the wavelet transform of PQRST segment by using wavelet distance on coefficients of wavelet for 35 individual dataset obtained from the database of MIT-BIH for getting an accuracy of 100 percent along with FAR of 83 percent and 86 percent FRR. All the subjects were healthy and the accuracy was obtained up to 81 percent with 12.5 percent FAR and the percentage of FRR for patients with arrhythmia was about 5.11 percent [46].

In 2009, a paper was published by Fatemian et al. on wavelet and template matching on a dataset of 14 healthy subjects obtained from database of MIT-BIH/PTB and ECG data was collected by 12 leads. HRV was addressed by authors in only two heartbeats/ subject with an accuracy of about 99.6 percent [47].Similarly, in 2014, a discrete wavelet transform was used by Tantawi et al. with a claim of 35 percent wavelet coefficients necessary for the identification purpose. To select features, information gain ratio was used with classification based on radial base neural network (RBNW). To test the algorithm, two publically available datasets were used. 51 subjects were used for the implementation of algorithm and an accuracy of about 95 percent was achieved. ECG data was collected with single lead and 40 out of 51 subjects belonged to the dataset of classical Fantasia [48].

In 2009, a paper was published by O. Boumbarov et al. in which they combined Hidden Markov Model with Gaussian Mixture Model (HMM-GMM) and also with Single Gaussian Model (HMM-SGM) to use them for detection of fiducial points by Conditional Random Field (CRF), and applied both LDA and PCA for reduction of dimensionality and the classifier used by them was radial based neural network. The accuracy achieved by them was in the range between 62 to 94 percent for different individuals [49]. Similarly, in 2010, the technique of Linear Predictive Coding (LPC) was used along with decomposition of wavelet packets and neural network for classification on a dataset of 15 private individuals with data collection of ECG signal with single leads in order to achieve an accuracy of 100 percent [50]. Additionally, in 2010, Odinaka et al. used a larger dataset of 269 individuals with data collection on single lead for achieving an accuracy of 76.9 percent and the EER was observed up to 5.58 percent. The whole work was used for the purpose of verification. They used Short Time Fourier Transform (STFT) to look the frequency components for extraction of features and the classification of features was done by log likelihood ratio [51].

In 2010, Discrete Wavelet Transform (DWT) along with Independent Component Analysis (ICA) were used by Ye et al. on three different datasets obtained from the databases of MIT-BIH Arrhythmia, MIT-BIH NSR and long term ST based on 118 subjects to extract 18 features. Features were reduced by PCA from 136 to 26 in addition with the help of SVM and Gaussian Radial Basis Function for achieving an accuracy of 99 percent with data collection with two leads and single heartbeat. Anyhow, an interval signal of five minutes was needed for each subject with FRR of 16 to 37 percent and the declaration of dataset was for maximum 65 individuals [52].

Similarly, HMM-GMM along with Hermite Polynomial Expansion was proposed in 2010 by Li et al. with an aim to extract features in ECG signal. The classifier used for this purpose was called Support Vector Machine and the accuracy achieved from their work was about 98.3 percent. Testing of system of done on a dataset of MIT-BIH comprised of 18 normal individuals with data collection through single lead electrodes [53]. Additionally, the next year in 2011, cluster based expectation minimization was proposed for the purpose of authentication by SuïňĄ et al. By compressing the ECG signal, a faster authentication was done with testing of algorithm on 30 individuals dataset obtained from MIT-BIH database. Template matching was used for classification of features and to reduce the features, Best ïňĄrst search (BFS) method was applied [54].

In 2010, extended Kalman filter was used by Ting et al. on a dataset of 13 individuals obtained from the database of MITBIH Arrhythmia. The classification of features was done on the bases of log likelihood score and data was collected through single lead ECG electrode to get an accuracy of about 87.5 percent. The algorithm was very robust to noise with SNR greater than 20 dB [55]. In 2012, Naraghi et al. also worked on extended Kalman filter to extract features for the purpose of identification. The classification of features was done on artificial neural network and the algorithm was test on a dataset of 10 subjects. The dataset was obtained from the database of MIT-BIH and data collection of ECG signal was done through single lead electrode with an identification rate of about 95 percent. Similarly, the next year in 2013, Sparse Coefficient vector was proposed by Wang et al. to extract features in ECG signal with a 1-NN classifier. A dataset of 100 subjects from the database of PTB was used for testing with a 99.4

Author	Features	Classifier	Year	Accracy	Subject	Leads
L, Biet et al	Fiducial	SMCA	2001	95 %	20	3-Leads
Israel et al	Fiducial	LDA	2005	100 %	29	12-Leads
Zhang et al	Fiducial	Baye's	2006	97.4 %	502	12-Leads
Wubbelier et al	Fiducial	Template Making	2007	98.1 %	74	3-Leads
Sibca et al	Fiducial	KNN	2007	99 %	26	1-Lead
Chan et al	Wavelet	Walvet Distance	2008	95 %	50	1-Lead
Bombarov et al	HMM-GMM	R8NN	2009	94 %	9	3-Leads
Ceutinho et al	Non-Fiducial	Cross Paring + MDL	2010	100 %	19	1-Lead
Loeng et al	LPC + WPD	Neutral Networks	2010	100 %	15	1-Lead
Odinaka et al	STFT	Log Liklihood Ratio	2010	76.9 %	269	1-Lead
Shen et al	Fiducial	Template Matching	2011	95 %	168	1-Lead
Chen et al	Choas Theory	BYNN	2014	91 %	19	1-Lead

Table 4.1: Public dataset of health people review table

percent accuracy. The limitations of their work were the data collection with single lead orientation with measurement in resting conditions.

4.2.3 Other Approaches for Features Extraction in ECG Signal

In 2014, Chaos Theory of feature extraction was presented by Chen et al. with uniqueness in chaotic attributes from the ECG signals. The Classification of these features was done through propagation neural network (PNW) and the algorithm was applied on a dataset of 19 subjects in normal healthy conditions from a private database. Orientation of single lead electrode was used for ECG signal collection with an accuracy of 91 percent [56].
Similarly, Legendre polynomial with a high order range from 2 to 6 was used by Khalil et al.in 2008. The approach was independent of fiducial detection and the algorithm was applied on a dataset of 10 individuals. ECG single was collected through an orientation of single lead ECG electrodes with an accuracy of 95 percent. Testing was done limited number of individuals with an observation of no false matching [57]. In 2010, combination of MDL with Merhave Cross Parsing was used by Coutinho et al. on a dataset of normal healthy 19 individuals obtained from a private database. Orientation of single lead ECG electrodes was used for data collection and they succeeded to get an accuracy of 100 percent. Each session contained cognitive tasks done on the individuals [58].

But, applications of biometrics based on ECG signal in real world have constraints like HRV due to physical activity of heart, emotions states of persons or other arrhythmia factors. Because of these constraints, challenges are faced by researchers in the temporal feature extractions in detecting fiducial points, therefore, they preferred to use approaches that are non-fiducial such as Fourier Transform, AC, or DC. Some researchers also used approaches based on DWT.
However, to address biometrics problems based on ECG due to HRV and other irregularities of heart need lot of work and attention for providing ECG as a feasible solution to real world challenges in identification of individuals particularly in healthcare security and privacy issues. These problems were addressed by many researchers by using the approach of non-fiducial detection that ended up with smaller rates of identification while using a dataset subset obtained from databases of NSR and ECGID. A picture of all these works is shown in Table 4 and Table 4.2.

4.3 Models for Effective Computing of ECG Signal

Recognition of emotion in the interaction of human with computer drew lot of attention during the early years of 1980. Right up to now, lot of work is done in the literature that was mainly focused on expression of face or analysis of speech for emotion detection purpose. Each of the work reported in this section of literature review, gives a clear understanding of emotions irrespective to the modality employed. However, more emphasis is on the biological signal processing for the purpose of detection and emotions classification [59].
However, the approaches used in the literature are different in their algorithm development with respect to the procedure applied experimentally. The methodologies used recently are divided into two different categories based on the approach the emotional models deployed and conceived. Discrete Emotional Models (DEM) included in the first category The ïňĄrst category includes discrete emotional models (that are mainly focused on the recognizing and labeling the standard emotional conditions such as happiness, sadness or feeling of fear depending on the applications. The reliance of these methods depends heavily on the assumption that any physiological state that is completely defined and distinguished from resting position. The second category includes Affective Dimensional Models (ADM) that relax the discrete emotional conditions and treat any affective state as two parameters combination called valence and arousal. The measurement of

Author	Features	Accracy	Dataset	Subjects	Leads
Palaniapan et al	RR Interval & Fiducial	97.6 %	MIT-BIH Arrhythmia	10	I-Lead
Chiu et al	Wavelet Coefficient of Signal	100 % Normal (87%)	MIT-BIH (NSR& Arr.)	35(NSR) & 10(Arr.)	I-Lead
Agrafioti et al	Autocorrelation	96.42 %	MIT-BIH (NSR & Arr.) & PTB	30(NSR)+13(Arr.)+13PTB	Lead II
Ting et al	EKF	87.5 %	MIT-BIH Arr.	13 Arr.	I-Lead
Ye et al	DWT+ICA	99 %	MIT-BIH (Arr. & NSR) and ST	65 max	2-Lead
Zeng et al	Reduced Binary Pattern	95.79 (Normal), 90.19 (Arr.)	MIT-BIH (Arr.& NSR)	8(NSR), 8(Arr.)	2-Leads
Islam et al	Heart Beat Shape	99.85 %	MIT-BIH Arr.	26 (Arr.)	I-Lead
Wang et al	QRS Complex	100 %	MIT-BIH Arr.	44(Arr.)	2-Lead
Proposed Work	DWT+HRV	95.85 %	MIT-BIH Arr.	47 (Arr.)	I-Lead

Table 4.2: Public dataset of people with heart diseases

emotional stimulation is called arousal and it is varied from a low to high value. Similarly, the measure of pleasing state is called valence and it is varied from a pleasant to an unpleasant condition. The measurement of these two parameters defines an AV plane that is a 2D space, and the areas of the plane are used for classification purpose that are needed for discrete emotional states [60].
There are pons and cons of both methodologies. For example, the conceptualization of DEM by individuals might be easy and fit to the applications, but, less robust in performance due to lack of defined physiological borders among the emotional states [59]. A literature review of both these methodologies is presented in rest of this section.

4.3.1 Discrete Emotional Models (DEM)

In 1983, Ekman et al. documented the first effort for the recognition of emotion by using the physiological signals. Their work made a breakthrough because they this work opposed the dogma dictates that none of autonomic nervous system activity is specific in emotions. It can also be said that their work gave some evidences that several human bodyâĂŹs reactions distinguish emotions. They studied six emotions such as surprise, disgust, sadness, anger, fear and happiness by using both expressional videos of face and physiological signals. They took the following biological signals for study: heart rate, temperature of left and right hand, resistance of skin, and muscle tension of forearm. Two recording modalities were used for respective feelings. The individuals were subjected to copy the emotional expressions after practicing in front of a mirror, and followed the operatorâĂŹs instructions concerning the muscles of face that were required for contraction. This all was done for getting the gestures of face. Similarly, an experience reliving procedure was followed for biological signals stimulation. To perform this task based on imagination, each and every individual was asked for relaxing and bringing to memory based on the personal experiences related to each of the emotions studied before. After completion of the task, the subjects were asked for ranking their feelings intensity on a scale that is predefined. 16 individuals were selected for performing this task, and among them 12 were actors by profession. The important thing to be noted that the use of actors in the task was to induce and analyze feelings as a standard practice in starting the effective research because they are able to manifest their natural emotions [60].
The statistical analysis based on the cardiovascular differentiation of emotions was reported by Sinha et al. in 1992. They used 27 individuals for

recording six indexes of heart related issues. They used the following biological signals: heart rate, blood pressure, volume of stroke, output of heart, resistance of peripheral vascular system, and contraction of myocardial muscles. The identification of cardiovascular patterns under 4 emotional expressions such as fear, anger, happiness and sadness was the main objective of their work [61].

An intelligent emotional system was proposed by Picard et al. in 2001 that was based on 4 biological signals information. The challenges in the field of affective computing were defined for the first time by their work. They also mentioned the fact in their work that the process of emotion detection is a sensitive process as compared to experimental work, and special attention is needed for this process. The reason is that for getting an affective valid information, it should be ensured that the emotion desired was induced and secondly, the labeling of subject should be done accurately [62].

In 2002, an experimental approach based on novelty was reported by Scheirer et al. for inducing and measuring frustrating emotion. There are several advantages of this novel approach in the problem of synchronization. A computer game was more precisely made instead of employing techniques based on images or audios to frustrate the user. The game failed at regular intervals of time that spoiled the pleasure of player and resulted into their frustration [63].

The idea of software interface adaption for current state emotion of a user by Nasoz et al. in 2003. They proposed a framework based on many models in combination with facial, verbal, gesture, and recordings of biological signals. The design of a synthesizer was accomplished for combination of all this information that provide a feedback to the user [64].

Similarly, experiments based on many trials were held by Kim et al. in 2004 for the purpose of emotions recognition. A dataset of 100 subjects were taken for testing. The reliance of method was on features out of the following three biological signal measurements such as temperature of skin, heart rate, and galvanic response of skin. A stronger relationship can be justified between ANS and these biological signals when subjected to some stimuli. The base of analysis was dependent on two different experiments; in first experiment 125 individuals of age range from 5 to 8 years participated and they were subjected to variety of audio and visual stimuli. For second experiment, a year later 50 more individuals in the same age range were taken to test the algorithm [65].

The detection of stress by using physiological signals based on driving tasks in real word was proposed by Healey et al. in 2005. The analysis of psychological status of a driver was the main purpose of their proposed system.

This work was based on an adaptive framework that was able to cope the stress of driver after diversion of cell phone calls to voice messages, and computer suggested an appropriate music and reduced the workload through the manipulation of navigating systems [66].
Benovoy et al. during the year 2008 gave another novel idea that was applicable in affective computing of systems based on recognition. The assessment of emotion in performance based applications was the main idea of their approach. The performance settings were like a musical act in which a performer was leading a musical instrument for composing an artistic output based on subject biological instantaneous reaction. There were two main phases of design. The first stage was based on recording of biological signals and the second one mapped these states of emotions. The classification of features was done through pressure of blood volume, galvanic response of skin, respiration for emotional states such as happiness, anger, pleasure and sadness. The purpose of second stage provided a rich external manifestation of internal status of emotions of the subject. The major aim of their work was building a musical instrument that was able to map the feelings of a user and was controllable by him or her [67].

4.3.2 Affective Dimensional Models (ADM)

The recognition of physiological emotions applicability in entertainment industry evaluation was proposed by Mandryk et al. in 2004. Their work proved that a different physiological response is found among the users when they play against their competitors, as compared to play against the computers. It is a natural fact that a different reaction is seen when playing against friends as compared to playing against some strangers [68]. Additionally, it was also observed that people love to play games when they play against human beings. The advantage of their work was to apply such type of technology in the industry of entertainment in order to design computer games and other virtual environments [69].
The same researchers in 2007, designed a constant mapping among emotional states and physiological measurements such as the AV plane. They were interested this time to identify the exact state of emotion like fun, excitement, frustration, challenge, and boredom. They adopted a fuzzy approach that was able to combine information from four physiological measurements such as galvanic response of skin, heart rate, smile, and EMG. After that combination, fruitful dimensions of valence and arousal dimensions were projected. According to their methodology, the establishment of a second fuzzy logic was designed for finding correspondence among the axes of AV plane and the

desired states of emotions [70]. The input was provided by four biological signals in the first fuzzy system. For this purpose, the requirement of a preprocessing step for ensuring the comparison of physiological measurements with one another was necessary. A moving average window was applied in the preprocessing step that has the ability to normalize the measurements between the range of 0 to 100 [70].
Similarly, in 2004, an ADM was proposed by Haag et al. that had the ability to classify the data based on the arousal and valence states. Their work included a physiological signals collection that were independently processed according to their characteristics specialty. The biological signals included in their work were EMG, galvanic response of skin, temperature of skin, pressure of blood volume, respiration and ECG [71].
In 2007, a paper was published by Jones et al. in which they proposed a framework for the purpose of recognition of affective states based on ADM. An emotional state could be characterized was the major idea through magnitudes of the states of arousal and valence deprived of their mapping to distinguished emotions such as happiness, sadness etc. They used two AV dimensional models on the basis of which the information was projected after their collection from biological signals [72].

4.4 Summary

In this chapter, a review of techniques used in the recognition based on emerging modalities was provided in the last few years. The summary of techniques utilized for datasets obtained from private databases. Though, for larger group of individuals, some of the better results were observed but there was also lack of some physical and physiological conditions were also found that operated intrusively with large number of lead proving little information about these databases some of these results represent better results for larger population, but lack in some other requirements like variety of subjects according to their age, gender etc. Additionally, the results obtained from datasets of public databases was shown in Table 4.1. The techniques applied in terms of cardiac disorders was provided in Table 4.2. The whole literature was divided into five sections; the first section gave information about fiducial techniques, the second was based on non-fiducial techniques, third gave some information about additional techniques, fourth represented the discrete dimensional models, and finally, affective dimensional models for information extraction from biological signals were presented.

Chapter 5

Design and Methodology

5.1 Preprocessing

This is the first step in design and methodology of the proposed system with an aim to remove noise from the ECG signal. During the process of recording, noise is added to the ECG signal because of various reasons such as electrodes displacement, breathing, and subject movements. Baseline drifts and interfaces of power lines result into these noises also that are regarded as low and high noise components. Additionally, electrodes also have built-in noise given by tolerance level provided by the manufacturer. Consequently, the inaccuracy of detection increases due to the onset and the offsets of the three complex waves P, QRS and T. The step of pre-processing includes detrend and normalization that improves significant probability of R-peak detection. The normalization is shown in equation 6 in which Y shows the input signal and the normalized output signal is represented by X.

$$x = \frac{y - min\,(y)}{max\,(y) - min\,(y)} \tag{5.1}$$

5.2 Feature Extraction

After preprocessing step, the normalized signals between the range 0 and 1 is obtained. Next step is the segmentation step that is followed by the detection of R-peak. The threshold for minimum peak height detection is kept up to 0.75 within the command of find peak in MATLAB. The proposed system utilized only 15 peaks from each waveform. The segmentation is done by moving 70 samples before and 140 samples after each R-peak. WPD algorithm is then applied to extract features from each segment obtained in prior step. Daubechies, Biorthogonal, Coiflets, and Symlets are four available families of wavelets that can be applied as filter banks. The shape of each wavelet is different but having similar fundamental characteristics. Because of having close shape to the ECG signal, Daubechies wavelet gives the best results. Convolution of the Daubechies function and original signal results into corresponding high-pass filter or a low-pass filter that are respectively known as the details and the approximations of the signal under examination. Extracting and keeping the important data of signal for analysis are the main objectives of finding features. Each signal is decomposed at depth 3 with db1 wavelet packets using Shannon entropy. Wavelet decomposition tree of proposed system is shown in figure 5.1.

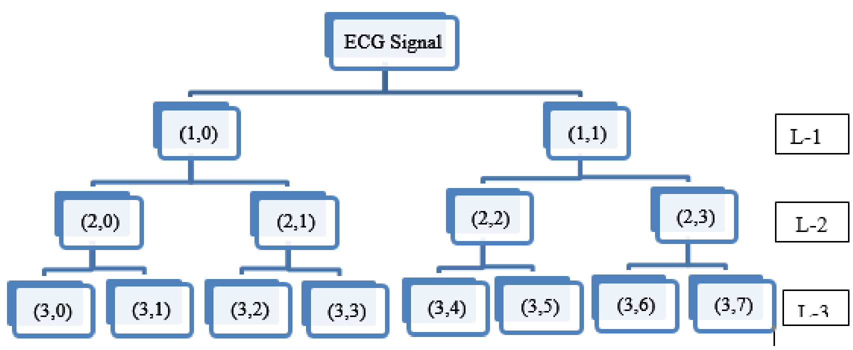

Figure 5.1: Wavelet Decomposition Tree

5.3 Feature Reduction and Classification

WEKA environment is used for reduction and classification of features that is particularly designed for algorithms of machine learning. To select useful attributes, Relief attribute evaluator that falls under the category of supervised attribute filter is applied. The flexibility of this evaluator is very high and it permits a variety of search and evaluation methods to be combined. Ranker search method is used in conjunction with relief attribute evaluator to find a subset of extremely interrelated features between similar classes having small inter-class correlation. This search method ranks attributes by their individual evaluations. Random forest classifier is applied with 10-fold cross validation by generating 100 trees to evaluate best performance of proposed strategy. In this classifier percentage split of data that is used for training and testing purposes are 66% and 34 % respectively.

5.4 Summary

This chapter covered the main design and methodology of the proposed system. The whole methodology includes three steps; the first step involves preprocessing of the data that includes noise removal from ECG signals, the second step involves the segmentation of features, and in the third step, the segmented features are reduced and classified. Figure 13 gives a depiction of overall wavelet decomposition tree of the proposed system.

Chapter 6

Results and Discussion

To determine the hit rate of the planned identification algorithm, an ample experiment was done on MIT-BIH arrhythmia database which comprises of 48 groups [73]. Double-lead ECG record is kept for 30 minutes, summing up to a whole of 24 hours of ECG data. This dataset consists of 47 subjects including 25 men aged between 32 to 89 and 22 women aged from 23 to 89. ECG data (dataset ID 201 and 202 attain from the same body). It has sampling rate of 360Hz and is saved by applying a '212' format over a 10mV range.
In this research 15 segments are extracted from heartbeat of every individual resulting a total of 705 instances. Number of instances predicted positive that are really positive is called true positive while number of instances predicted positive that are in fact negative is known as false positive. Recall is the true positive rate also referred to as sensitivity. Precision is the ratio between true positive and predicted positive and it is also referred to as positive predictive value (PPV). F-Measure is a combination of precision and recall measurement by calculating their harmonic mean. Out of 705 instances, correctly and incorrectly classified instances are 653 and 52 respectively giving 92.62% accuracy. Table 6.1 provides the complete outcome of this research. The confusion matrix is commonly known as contingency table. We have 47 classes which leads to 47ÃŮ47 confusion matrix. Sum of properly classified instances is represented by the diagonal of the matrix. Confusion matrix is

TP Rate	FP Rate	Precision	Recall	F-Measure	Accuracy
0.926	0.002	0.933	0.926	0.923	92.62 %

Table 6.1: Summary of results

plotted using MATLAB shown in figure 6.1.

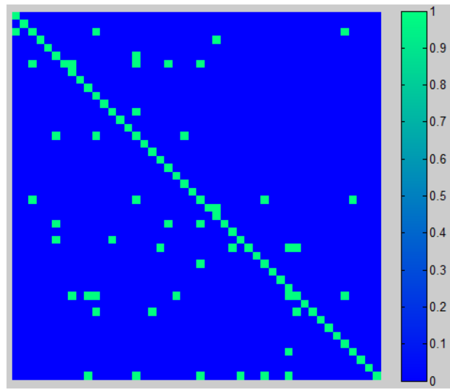

Figure 6.1: Plot of Confusion Metrix

Chapter 7

Conclusion and Future Works

This research work advocated the feasibility of ECG based biometric systems that has the ability to overcome many privacy and security challenges and loopholes furnished by traditional techniques of identification and even other evolving techniques of identification. The most recently faced challenges were explored in this thesis related to ECG based biometrics after reporting the best results and abilities to handle the mentioned challenges. HRV is the most common challenge that is caused by some irregularities of heart, emotional or physical activity of an individual. MATLAB is used for overcoming this challenge and removing HRV in ECG signals.
The other challenge in real world ECG based biometrics is somehow invasive nature of the process of its acquisition. In this research double lead ECG strategy is used to make it non-invasive for the users. Additionally, instead of using fiducial approach wavelet based technique is demonstrated in the thesis. The approach based on wavelets improves the overall accuracy of the system and also provides a feasible feature extraction solution in people having cardiac problems. In this research 15 segments are extracted from heartbeat of every individual resulting a total of 705 instances. Number of instances predicted positive that are really positive is called true positive while number of instances predicted positive that are in fact negative is known as false positive. Recall is the true positive rate also referred to as sensitivity. Precision is the ratio between true positive and predicted positive and it is also referred to as positive predictive value (PPV). F-Measure is a combination of precision and recall measurement by calculating their harmonic mean. Out of 705 instances, correctly and incorrectly classified instances are 653 and 52 respectively giving 92.62% accuracy. The confusion matrix is commonly known as contingency table. We have 47 classes which

leads to 47 x 47 confusion matrix. Sum of properly classified instances is represented by the diagonal of the matrix.

Apart from being tackled with research challenges we demonstrate the effectiveness of ECG based technology over other popular and widely deployed biometric technologies by providing uniqueness of ECG based system. One of the most important factor is its inherent property of liveness detection which make the system more robust against various vulnerabilities such as HRV and Arrhythmia etc. Similarly, ECG contain properties that best suits for its selection as biometric like its high uniqueness, permanence, universality and acceptability etc.

This research also helps in opening wide range of possibilities applicable to improve efficiency of the system. Because we demonstrate complete procedure of algorithmic approach with varying parameters for the in depth analysis of proposed strategy. For this purpose, we analyze the results based on both ïňĄducial based and wavelet features based techniques over the same databases and conditions for fair conclusion. This suggest the dominance of wavelet based features over fidicuial features due to its power of extracting features both in time and frequency domain. Another conclusion drawn from the use of novel HRV features for arrhythmic database, both solely and with the combination of DWT for fair comparison. Similarly, effectveness about type of wavelet family function used for feature extraction was also tested and compared to conclude the optimal choice of Haar wavelet co-efficient with level 5 decomposition is best suited for the system. Segmentation window size of 95 samples and number of classifier trees in case of random forests have been concluded for efficient results.

7.1 Conclusive Points

All of the above conclusions can be summed up as the following points.

- This research provides a user friendly and non-invasive approach for acquisition process in ECG biometrics using only a single lead of ECG data.
- This research also proposed a ïňĄducial independent approach which requires less computational complexity and enhanced accuracy.
- Provide a generalized solution for both healthy databases and population having cardiac irregularities.

- Wavelet based feature approach with Haar coeïňČcients of level 5 is suggested as the most optimal solution in terms of accuracy and convenience.
- Random forest and KNN (KNN as a simple time effective algorithm) are presented as classiïňĄer for better performance with adjustable number of forest trees and segmentation window size.
- HRV artifact removal and hybridization of HRV features with DWT features are suggested to cope with various challenges.

7.2 Future Dimensions

- To make the proposed system industrially and commercially viable, ECG signal can be used with some other biometric such that the new multi modal approach take advantage of various advantages provided by both techniques. This combination of intrinsic property of ECG with some extrinsic property such as voice or iris could result in better performance as well as suggesting solution which can both be robust for better security and capable for widely deployment in real world applications.
- Different emotional and physical states can be analyzed on the basis of heart rhythm, so to compensate that emotional or physical state effect from the signal for better presentation as biometric solution.
- This research also suggests the combination of various features in order to extract more accurate and useful information about the unique behavior of cardiac pattern.

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