

**ELECTROCARDIOGRAM BASED HEART DISEASE DIAGNOSIS
USING ARTIFICIAL INTELLIGENCE**

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ABSTRACT

Heart diseases have been the major cause of deaths in the world according to a recent study. The main tool that is widely used to understand the cardiac condition is an Electrocardiogram (ECG). Normal and abnormal cardiac function of the human heart can be analyzed through the application of the ECG signal processing and evaluation. Although traditionally the interpretation of these signals remains largely a manual effort, as computing power has increased, so too has the application of computational methods for ECG evaluation and classification. Therefore, it is necessary to have suitable methods for early detection of heart condition of the patient. In addition, the ECG is recorded on a thermal paper, which cannot be stored for a long time, because thermal trace over time tends to erase gradually. However, some hospitals are saving the ECG thermal papers as scanning images in the electronic equipment's (like computers) to maintain medical records, but this method requires too high memory capacity, in addition to use low scanning resolution that gives ECG image unclear when preview. In this thesis, image-processing techniques are developed for the ECG feature extraction and signal regeneration as a digital time series signal. The first step is to use a flatbed scanner to take an image of the ECG signals; during this step the bit depth, the image resolution and output file format are a main concern. There are chances that the image may be blurring or suffer from some chromatography ambiguity due to unclear original image. Therefore, a new method for enhancing the image contrast called Fuzzy Hyperbolic Threshold is proposed with a new membership equation. This method has significant impact on the adjustment of lighting in dark images, clarifies its edges, clarifies their features, and improved image quality. In addition can use this method on different types of medical images, and the simulation results have been a very good when compared with the other methods that can used in the image contrast enhancement. Accordingly, the first step is an image segmentation method using proposed thresholding algorithms has been used to locate objects and boundaries of the ECG signal and background grid lines in the ECG images. This technique is used to transform the data of the ECG signal recorded on paper to a digital time series database. The ECG signal is usually infected with various kinds of noise such as Baseline Wander (BW) noise, Motion Artifacts (EA) noise, Muscle Artefacts (MA) noise, and Power Line Interference (PLI) noise. The useful and powerful techniques that use to analyze such this type of signals are an adaptive Wavelet filter. The distortion in the S-T segment of ECG signal can be minimized by applying a new technique, which is, amalgamates the adaptive filter and hybrid soft computing technique known as Discrete Wavelet Transform (DWT) for BW noise removal. After noise removal, the data from the ECG is to be acquired; for this purpose a method is devised based on DWT. Third stage is the features extraction; proposed a special domain based on DWT to extract diagnostic information from the ECG signal. Symlet transform (one of the wavelet transform families) was used for acquiring the desired data from ECG signals and achieved 99.50% productivity and 99.87% sensitivity. Finally, five different types of the ECG diseases are identified using various artificial intelligence types like hybrid RBFNN and hybrid PSO-RBFNN. The optimal neural network model (PSO-RBFNN) has 13 input nodes, 40 hidden nodes, and 5 output nodes signifying Angina, RBBB, MI, Normal and LBBB. The classification performance was carried out with 99.59% for specificity and 98.37% for sensitivity.

ABSTRAK

Penyakit jantung telah menjadi penyebab utama kematian di dunia ini berdasarkan kajian terkini. Peralatan utama yang digunakan secara meluas untuk memahami keadaan kardiak ialah Elektrokardiogram (ECG). Fungsi kardiak jantung manusia yang normal dan tidak normal boleh dianalisa melalui aplikasi pemprosesan isyarat dan penilaian ECG. Walaupun secara traditional penafsiran isyarat-isyarat ini adalah secara manual, apabila kuasa perkomputeran bertambah, begitu juga aplikasi kaedah pengiraan untuk penilaian dan klasifikasi ECG. Oleh itu, kaedah-kaedah yang sesuai untuk mengesan keadaan awal jantung adalah perlu. Tambahan lagi, ECG direkod di atas kertas termal, dimana ia tidak boleh disimpan lama kerana kesan termal akan terpadam secara beransur-ansur mengikut masa. Walau bagaimana pun, sesetengah hospital menyimpan kertas termal ECG sebagai imej yang diimbas di dalam peralatan elektronik (seperti komputer) untuk mengekalkan rekod perubatan, tetapi kaedah ini memerlukan kapasiti memori yang terlalu tinggi disamping menggunakan revolusi pengimbasan yang rendah yang memberikan imej yang tidak jelas apabila dipratontonkan. Di dalam tesis ini, teknik pemrosesan imej dibangunkan untuk mengestrak ciri-ciri ECG dan penjana semula isyarat sebagai isyarat siri masa digital. Langkah pertama ialah dengan menggunakan pengimbas *flatbed* untuk mengambil imej isyarat-isyarat ECG; ketika langkah ini kedalaman imej, resolusi imej dan format saiz output adalah menjadi kebimbangan utama. Adalah berkemungkinan imej akan kabur dan mengalami kromotografi kekaburan disebabkan oleh imej asal yang tidak jelas. Maka itu, kaedah baru untuk meningkatkan kontra imej yang dipanggil Ambang Hiperbolik Fuzzy (*Fuzzy Hyperbolic Threshold*) adalah dicadangkan dengan persamaan keahlian baru. Kaedah ini mempunyai impak yang penting kepada pengubahsuaian pencahayaan di dalam imej gelap, penjelasan bucu, penjelasan ciri dan memperbaiki kualiti imej. Tambahan lagi, kaedah ini boleh digunakan pada imej-imej perubatan yang berlainan, dan hasil simulasi adalah sangat bagus berbanding dengan kaedah-kaedah lain yang boleh digunakan untuk meningkatkan kontras imej. Sewajarnya, peringkat pertama ialah kaedah segmentasi imej menggunakan algoritma pengambangan yang telah dicadangkan untuk mengesan objek dan sempadan isyarat ECG dan garisan grid latar belakang didalam imej ECG. Teknik ini digunakan untuk mengubah data isyarat ECG yang direkod diatas kertas kepada pengkalan data siri masa digital. Isyarat ECG selalunya terkesan dengan pelbagai jenis bunyi seperti bunyi *Baseline Wander (BW)*, bunyi *Motion Artifacts (EA)*, bunyi *Muscle Artefacts (MA)*, dan bunyi *Power Line Interference (PLI)*. Teknik berguna dan berkuasa yang pernah digunakan untuk menganalisa isyarat jenis ini adalah penapis Wavelet penyesuaian. Herotan di dalam segmen S-T bagi isyarat ECG boleh diminimumkan dengan menggunakan teknik baru yang menggabungkan penapis penyesuaian dan teknik pengkomputeran hibrid lembut dikenali dikenali sebagai *Digital Wavelet Transform (DWT)* untuk menyingkirkan bunyi BW. Selepas bunyi disingkirkan, data diambil daripada ECG, kaedah

berdasarkan DWT digunakan untuk tujuan ini. Peringkat ketiga ialah pengekstrakan ciri-ciri, dicadangkan domain khas istimewa digunakan pada DWT untuk mengesktrak maklumat diagnostik daripada isyarat ECG. Pengubah Symlet (salah satu keluarga pengubah wavelet) telah digunakan untuk mendapatkan data yang dikehendaki dari isyarat-isyarat ECG dan mencapai produktiviti 99.50% serta kepekaan 99.87%. Akhirnya lima jenis penyakit ECG dapat dikenalpasti menggunakan pelbagai teknik kepintaran buatan seperti hibrid RBFNN dan hibrid PSO-RBFNN. Model rangkaian neural optima (PSO-RBFNN) mempunyai 13 nod input, 40 nod tersembunyi dan 5 nod output menandakan Angina, RBBB, MI, Normal dan LBBB. Prestasi klasifikasi dijalankan dengan spesifisiti 99.59% dan kepekaan 98.37%.

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LIST OF NOMENCLATURES

Symbol	Meaning and units
b	Biases
c	Column
$C1$ & $C2$	Acceleration coefficients
D	Desired output
E	Error
exp	Exponential
$f(x)$	Function
f_s	Sampling frequency
$gBest$	Global best position for PSO
h	Hidden layer
Hz	Hertz
m	Membership function
mV	Millivolt
P	Position
P_+	Positive predictivity
$pBest$	Best previous position
r	row
r_1 & r_2	Random numbers
S_e	Statistical parameters sensitivity
sec	Second

V	Velocity
w	Weight
X_n	Normalized
Z	Z-transform
α	Constant
μV	Microvolt
$\phi(x)$	Output of the hidden layer
σ	Standard deviation

LIST OF ABBREVIATIONS

AF	Adaptive Filter
AHA	American Heart Association
AIWF	Adaptive Inertia Weight Factor
AL	Aluminum
ANC	Adaptive Noise Canceller
ANN	Artificial Neural Network
AV	Atrioventricular
BW	Baseline Wander
CAD	Computer Aided Design
CAE	Computer Aided Engineering
CDC	Disease Control and Prevention Centers
CPSO	Chaotic Particle Swarm Optimization
CWT	Continues Wavelet Transform
dpi	Dots per inch
DWT	Discrete Wavelet Transform
EA	Motion Artifacts
ELM	Extreme Learning Machine
FFT	Fast Fourier Transform
FN	False Negative
FP	False Positive
GA	Genetic Algorithm
HP	Heartbeat

HPF	High Pass Filter
IDWT	Invers Discrete Wavelet Transform
LMA	Levenberg Marquardt Algorithm
LMS	Least Mean Square
LPF	Low Pass Filter
MA	Muscle Artefacts
MLP	Multi-layer Perceptron
MSE	Mean Square Error
NN	Neural Network
PLI	Power Line Interference
ppi	Pixels per inch
PSO	Particle Swarm Optimization
RBFNN	Radial Basis Function Neural Network
SA	Senatorial
SD	Stander Deviation
SI	Swarm Intelligence
SNR	Signal to Noise Ratio
TB	Total Analyze Peaks
TP	True Positive
Val	Validation
WAF	Wavelet Adaptive Filtering
WT	Wavelet Transform

CHAPTER ONE

INTRODUCTION

1.1 INTRODUCTION

Biomedical signal and image processing has been the topic of research and study for the past ten years. Diagnostic interpretation and processing of signals or images can be carried out using many different applications. Some examples of biomedical image/signal processing, such as visual analysis of long-term Electrocardiogram (ECG) image/signal (sometimes called Holter signal) (Dallali et al., 2011), analysis of sleep Electroencephalogram (EEG) that is tedious, time-consuming and operator dependent (Sadish et al., 2014; Boualemet al., 2011), and analysis of Electromyography (EMG) signal to control the prosthetic arm/hand (Mohammad et al., 2014; Rubana et al., 2013). Another example is the Magnetic Resonance Imaging (MRI) that have played an increasingly important role in the investigation of brain structure, function, development and pathologies (Karl et al., 2014; Parveen et al., 2012). It is obvious that automated systems techniques based-computer for biological image (and / or signal) processing such as noise removal, pattern detection and disease classification and its diagnosis, etc. These reasons and others make us think about the development of more computer-based algorithms to assist physician's in the accurate diagnosis of complex diseases in the heart patients. Therefore, reduces the amount of physician's time needing to spend for deciding on the diagnosis of complex diseases, as well as the accuracy of the diagnosis. The increased interest in computer-aided image/signal processing methods, still there is a greater need for developing more techniques in biomedical engineering.

Different technologies play an important role in acquiring information from the ECG printout paper and then extract the signals and transferring them into real time digital signals through the use of computers. Thus, gives an important advantage in the applications different technology areas. Such as, digital signal transmission over the Internet to another location. In addition to, the storage capacity requirement is also not much as the digital data can easily be stored in smaller spaces and can easily be recalled. Thereby saving time, effort and cost.

In this thesis, computer-based methods for extraction, analysis and interpretation of biological Electrocardiogram (ECG or EKG) signals have been subject of intense research. The ECG signal analysis carried out through a computed mathematical model is considered as the most economical solution for extraction, analyzing and interpreting the ECG signals and helping in future designs. In addition to highlighting the technical problems in previous studies, which are in the same thesis approach, it found that most of the efforts are focused in the area of pre-processing of the ECG paper images, and how to extract the ECG signal and convert it to digital format. Due to the many benefits physicians have by using computer based technology for analyzing and interpreting the ECG signals, the physicians greatly support the use of computer based technology for disease diagnosis and analysis. Thereby, increasing the support of physicians in diagnosing of heart disease. One example of computer-based methods for early diagnosis of heart disease is Artificial Neural Networks (ANN), is one of the efficient methods, and it can be regarded as one of the most recent techniques in this field, and has primarily been considered for classification of ECGs into different diagnostic groups. It has been shown that ANNs for specific issues can perform better than both experienced cardiologists and ruled criteria. The researchers continue their research in finding and developing more advanced and feasible system which not only be more accurate but will be economical and also minimize manual efforts (Tanis et al., 2011; Hosseini et al., 2006).

1.2 BACKGROUND

The Electrocardiogram (ECG) is a bioelectric signal that records the electrical activities of the heart muscle, and transmitted to the body surface as electrical events in the form of signals, captured and externally recorded by an Electrocardiography device (Martin et al., 2004). These signals providing direct evidence of cardiac aspects of myocardial anatomy, functions and blood supply (Branislav et al., 2013; Anuradha and Veera, 2008). Therefore, the ECG provides helpful information about the functional aspects of the heart and cardiovascular system, Figure 1.1 shows the basic trace of the ECG. The state of cardiac health is generally reflected in the shape of ECG waveform and heart rate (Barbara et al., 2014). It may contain important pointers to the nature of diseases afflicting the heart. Since, the ECG records are non-stationary signals, this indication may occur at random in the time scale. In this situation, the disease symptoms may not come all the time, but would manifest at certain irregular intervals during the cycle. Therefore, for effective diagnostics, the study of ECG pattern and heart rate variability signal may have to be carried out over several hours (Abdelhamid et al., 2012).

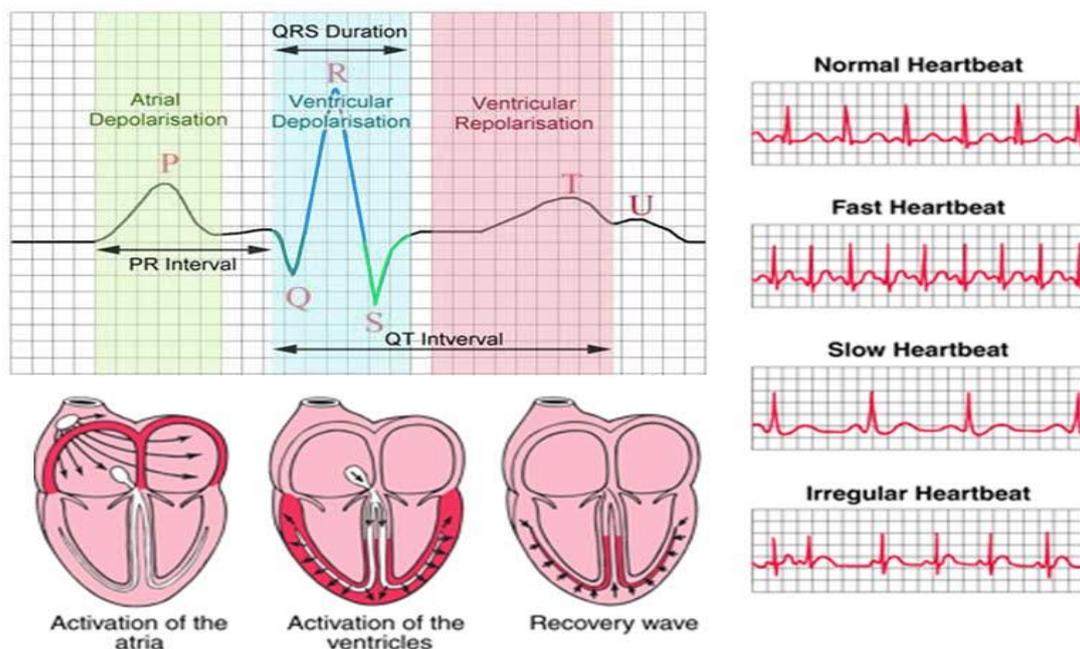


Figure1.1: ECG trace and basics.

Source: Tamarkin D., (2011).

ECG signals can be recording from the human body using different methods; among the methods 12-lead ECG recording method is widely used and is considered as the best method for diagnosing different heart diseases (Stefan, 2005). After obtaining the 12-lead ECG recording as shown in the Figure 1.2, doctors and physicians can carry out the analysis and diagnosis of a disease through manual visualization of the ECG signal (John, 2005; Lippincott and Wilkins, 2011). Utilizing personal experience and knowledge to make diagnostic decision can cause difference in diagnosis, in addition to the time required for making this diagnostic decision will also be long. However, the process of decision-making can be very difficult for the new physicians specialist in the heart disease and non-specialists of heart disease that they working at remote areas (Jonathan et al., 2010). Thus, this method of diagnosing the 12-lead ECG interpretation can lead to wrong diagnosis of the disease in certain cases (John, 2005). Therefore, a system must be developed which would be able to read out the ECG signal and diagnose it accurately. This would also make the process of diagnosing a disease much quicker and accurate and moreover, there will be no confusion in admitting the accuracy of the result. All the physicians will agree and accept the results presented by the system and will aid them to take necessary actions to treat the patient immediately; as delay in treating heart, problems can lead to severe circumstances.

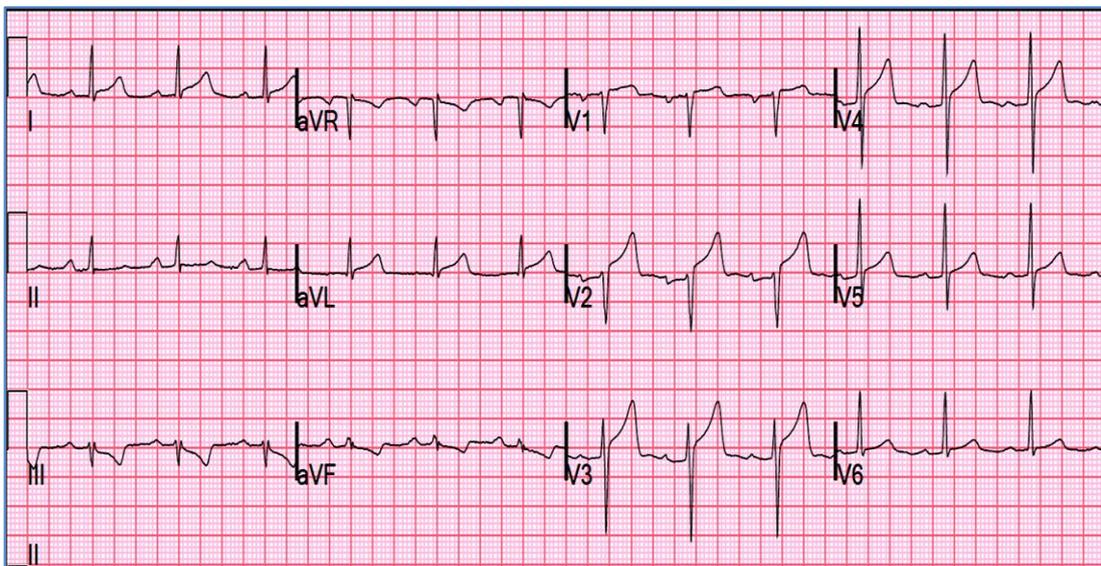


Figure1.2: Typical 12-lead ECG signal.

Source: ECGpedia, (2008)

CHAPTER ONE

INTRODUCTION

1.1 INTRODUCTION

Biomedical signal and image processing has been the topic of research and study for the past ten years. Diagnostic interpretation and processing of signals or images can be carried out using many different applications. Some examples of biomedical image/signal processing, such as visual analysis of long-term Electrocardiogram (ECG) image/signal (sometimes called Holter signal) (Dallali et al., 2011), analysis of sleep Electroencephalogram (EEG) that is tedious, time-consuming and operator dependent (Sadish et al., 2014; Boualemet al., 2011), and analysis of Electromyography (EMG) signal to control the prosthetic arm/hand (Mohammad et al., 2014; Rubana et al., 2013). Another example is the Magnetic Resonance Imaging (MRI) that have played an increasingly important role in the investigation of brain structure, function, development and pathologies (Karl et al., 2014; Parveen et al., 2012). It is obvious that automated systems techniques based-computer for biological image (and / or signal) processing such as noise removal, pattern detection and disease classification and its diagnosis, etc. These reasons and others make us think about the development of more computer-based algorithms to assist physician's in the accurate diagnosis of complex diseases in the heart patients. Therefore, reduces the amount of physician's time needing to spend for deciding on the diagnosis of complex diseases, as well as the accuracy of the diagnosis. The increased interest in computer-aided image/signal processing methods, still there is a greater need for developing more techniques in biomedical engineering.

Different technologies play an important role in acquiring information from the ECG printout paper and then extract the signals and transferring them into real time digital signals through the use of computers. Thus, gives an important advantage in the applications different technology areas. Such as, digital signal transmission over the Internet to another location. In addition to, the storage capacity requirement is also not much as the digital data can easily be stored in smaller spaces and can easily be recalled. Thereby saving time, effort and cost.

In this thesis, computer-based methods for extraction, analysis and interpretation of biological Electrocardiogram (ECG or EKG) signals have been subject of intense research. The ECG signal analysis carried out through a computed mathematical model is considered as the most economical solution for extraction, analyzing and interpreting the ECG signals and helping in future designs. In addition to highlighting the technical problems in previous studies, which are in the same thesis approach, it found that most of the efforts are focused in the area of pre-processing of the ECG paper images, and how to extract the ECG signal and convert it to digital format. Due to the many benefits physicians have by using computer based technology for analyzing and interpreting the ECG signals, the physicians greatly support the use of computer based technology for disease diagnosis and analysis. Thereby, increasing the support of physicians in diagnosing of heart disease. One example of computer-based methods for early diagnosis of heart disease is Artificial Neural Networks (ANN), is one of the efficient methods, and it can be regarded as one of the most recent techniques in this field, and has primarily been considered for classification of ECGs into different diagnostic groups. It has been shown that ANNs for specific issues can perform better than both experienced cardiologists and ruled criteria. The researchers continue their research in finding and developing more advanced and feasible system which not only be more accurate but will be economical and also minimize manual efforts (Tanis et al., 2011; Hosseini et al., 2006).

1.2 BACKGROUND

The Electrocardiogram (ECG) is a bioelectric signal that records the electrical activities of the heart muscle, and transmitted to the body surface as electrical events in the form of signals, captured and externally recorded by an Electrocardiography device (Martin et al., 2004). These signals providing direct evidence of cardiac aspects of myocardial anatomy, functions and blood supply (Branislav et al., 2013; Anuradha and Veera, 2008). Therefore, the ECG provides helpful information about the functional aspects of the heart and cardiovascular system, Figure 1.1 shows the basic trace of the ECG. The state of cardiac health is generally reflected in the shape of ECG waveform and heart rate (Barbara et al., 2014). It may contain important pointers to the nature of diseases afflicting the heart. Since, the ECG records are non-stationary signals, this indication may occur at random in the time scale. In this situation, the disease symptoms may not come all the time, but would manifest at certain irregular intervals during the cycle. Therefore, for effective diagnostics, the study of ECG pattern and heart rate variability signal may have to be carried out over several hours (Abdelhamid et al., 2012).

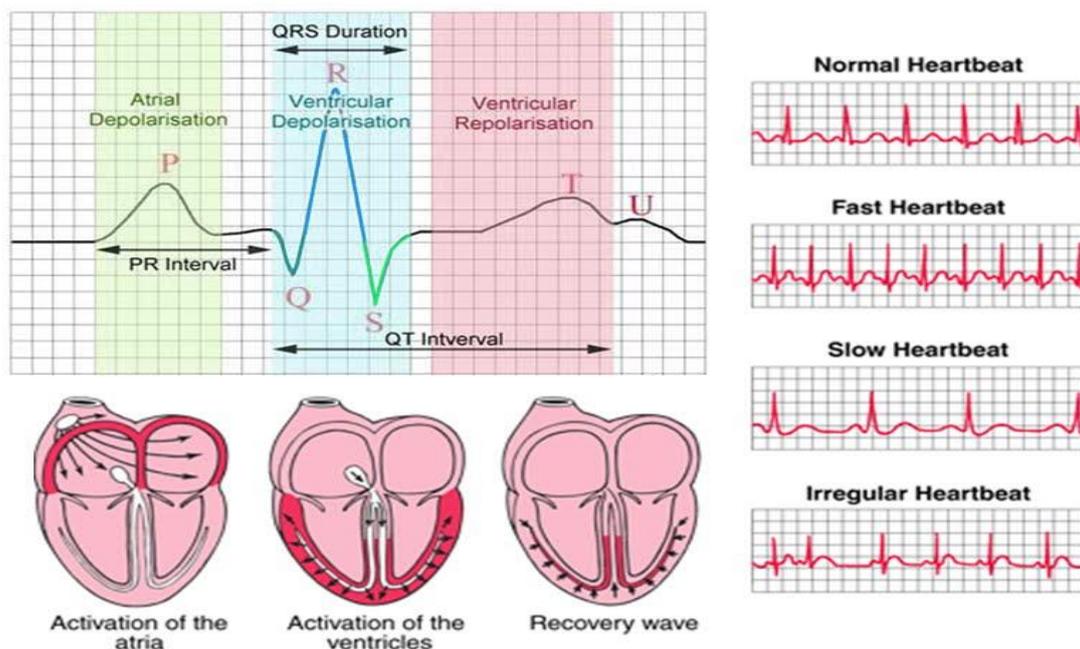


Figure1.1: ECG trace and basics.

Source: Tamarkin D., (2011).

CHAPTER THREE

METHODOLOGY

3.1 INTRODUCTION

This chapter presents the traditional with our proposed algorithms (new approach) of preprocessing and feature extraction steps for an ECG to convert it from image to digital signal presented in details. In addition, the artificial intelligent algorithm used to construct a better model for best performance diagnostics. Finally, computational models will be presented, and the simulation steps and facilities used for database collection are presented.

3.2 STRATEGY OF FRAME WORK

Figure 3.1 describes the main strategic framework of this study. The strategy framework consists a four main panels, are capturing (data acquisition) panel, pre-processing panel, feature extraction panel and the artificial intelligent for diagnostic panel. Each panel contains several algorithms and processing techniques, some of which are traditionally it has been used directly without any change, and the others has been applied with some changes and modifications that serve our research, and others proposed as a new technique. The results were clarified via well technique based on this flowchart. The outcomes of this framework strategy are summarized in the conclusions and recommendation for future studies.



Figure 3.1: Main strategic framework of the study.

3.3 EXPERIMENTAL DATA SET

There are many ECG databases available online on the internet web sites, which are used by the computer-aided researchers in their research to ECG interpretation and classification. So there are several ECG databases that is most commonly used, which is MIT-BIH arrhythmia database, CSE multi-lead database and AHA database (Zhang et al. 2009; Llamedo and Martínez, 2007).

In this thesis, the data were collected through fieldwork from the Ibn Al Bitar Cardiac Center and the Ibn Al Nafis Cardiac Center from Baghdad-Iraq (186 cases). The ECG data are real copies was taken from the hospital database, and was putting the diagnostics notes by the specialist doctor on each one of them. In addition to freely available on MIT-BIH arrhythmia database-PhysioNet-PhysioBank-Signal Archives-ECG (140 cases), and. In addition to 73 cases from ECG-pedia online (ECG-Pedia, 2008), which has been provided by Dr. Alberto Giniger, chief of the Electrophysiology and Arrhythmias department of the Cardiovascular Institute of Buenos Aires (ICBA), Argentina (Alberto et al., 2014; Llamedo and Martínez, 2009). The data used for the PhysioNet/CINC-Challenge-2013 consisted of Hundreds of 12-lead ECGs, each 10 seconds long, with standard diagnostic bandwidth (0.05-100 Hz). The 12 leads (I, II, III, aVR, aVF, aVL, V1, V2, V3, V4, V5 and V6) were obtained simultaneously; each was recorded at 500 samples per second, 16 bits per sample, with 5V resolution (MIT-BIH Database).

3.4 ECG IMAGE ACQUISITION

The algorithm starts with the ECG recording image that determined by the user. The developed capturing panel provides three different methods to use the image as the input for the following image pre-processing panel. Firstly, the user can use an optical scanning technology to scan the ECG paper at 600/300/200 dpi (pixel or dots per inch) and stored as a color image in many types of format files such as (JPEG, BNG... and GIF). Traditionally, the preferred algorithm for the image compression is JPEG (Huy, 2009; David, 2012). Secondly, the user can get the snapshot of ECG signal from the ECG machine through activation the real time operating; also, the image can be obtained from