UNIVERSITI PUTRA MALAYSIA

A ROBUST HIGH ACCURACY CARDIOVASCULAR DISEASE DETECTION SYSTEM BASED ON ECG ENERGY CONCENTRATION TIME-FREQUENCY ANALYSIS SUPPORTED BY THRESHOLD AND INTELLIGENT CLASSIFIER

AHMED FAEQ HUSSEIN

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By

AHMED FAEQ HUSSEIN

Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in Fulfillment of the Requirements for the Degree of Doctor of Philosophy

June 2018

DEDICATION

To the soul of my father and to my dear mother who have taken great pains to growing me up

And

To my teachers who providing me with best education

Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfilment of the requirement for the degree of Doctor of Philosophy

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Globally, cardiovascular diseases (CVDs) are the primary cause of deaths. According to the most recent statistics of the World Health Organization (WHO), CVDs mortality rates are expected to range between 246 deaths for 100,000 population in 2015 to 264 for 100,000 population in 2030. Reportedly, nearly half of them do not indicated any prior symptoms or experienced any pain of heart attack. Moreover, about 25% of CVDs patients were unable to get timely medical aid at the critical time especially those who experienced heart problems at the late stages and who live in remote places. High accuracy out-of-hospital detection of CVDs is, therefore, vital to prevent complications of the heart that may lead to sudden death or disability. Electrocardiogram (ECG) represents cardiac condition as electrical signal waveforms. However, the interpretation of these waveforms is still very challenging because the signals are mainly composite of eight different signals from various heart components namely atriums, ventricles, sinus node, AV-node, and common bundles. The non-stationary and multi-frequency nature of ECG signal waveforms makes the use of Time-Frequency Distributions (TFDs) for analysis, inevitable.

The main aim of this study is to develop a high accuracy scheme for CVDs detection, including ischemia and arrhythmia, for multi-lead and long intervals ECG signal waveforms. The scheme is based on non-linear TFD analysis supported by threshold technique and intelligent machine learning classifier namely Support Vector Machine (SVM). In addition to the new TFD scheme, the use of multi-leads instead of single lead, and 1-minute interval instead of beats or frames for classification, contributes to the improvement of detection performance. In addition to the venerable MIT database, a 7-lead low power ECG device is also designed and implemented. It is used for raw ECG data acquisition to further evaluate the proposed scheme for the ECG data outside the MIT ECG database and enable the real-time CVDs detection capability. The ECG data collected from this device have also been evaluated for both normal and abnormal cases. The proposed scheme is examined and evaluated with various normal and abnormal ECG cases that cover CVDs namely arrhythmia and ischemia. The datasets used in this study comes mainly from MIT ECG database where it is used for the classifier training and performance evaluation as well.

The proposed scheme contributes to a very high overall accuracy, sensitivity and specificity of more than 99% for CVDs detection. The results for arrhythmia detection are 99.39% accuracy, 99.38% sensitivity, and 99.44% specificity. The results for ischemia detection are 99.10% accuracy, 99.09% sensitivity, and 99.13% specificity. These results indicate that the proposed scheme is suitable for CVDs detection and can be an excellent platform for automated CVDs detection systems providing on-demand or continuous monitoring for long time duration at high accuracy.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

SISTEM PENGESANAN PENYAKIT KARDIOVASKULAR TEGAP BERKETEPATAN TINGGI BERDASARKAN ANALISIS MASA-FREKUENSI KEPEKATAN TENAGA ECG DISOKONG DENGAN PENGELAS AMBANG DAN PINTAR

Oleh

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Secara global, penyakit kardiovaskular (CVD) merupakan antara penyebab utama kematian. Menurut laporan statistik terkini Pertubuhan Kesihatan Sedunia (WHO), kadar kematian penyakit CVD dijangka berlaku sebanyak 246 kematian bagi penduduk seramai 100,000 orang pada 2015 sehingga 264 kematian bagi 100,000 orang pada 2030. Hampir separuh daripada pesakit kardiovaskular tidak mengalami sebarang gejala awal atau serangan jantung. Tambahan lagi, hampir 25% pesakit CVD tidak mendapat bantuan perubatan pada waktu kritikal, terutamanya pesakit yang menghidapi masalah jantung pada tahap terakhir dan tinggal di kawasan pedalaman. Oleh itu, ketepatan pengesanan CVD di luar hospital adalah penting bagi mengelak komplikasi jantung yang boleh membawa kepada kematian mengejut atau kehilangan upaya. Elektrokardiogram (ECG) memaparkan keadaan jantung dalam bentuk gelombang isyarat elektrik. Walau bagaimanapun, mentafsir bentuk gelombang itu masih merupakan satu cabaran kerana sebahagian besar isyarat tersebut merangkumi lapan isyarat berbeza daripada pelbagai komponen jantung, iaitu atrium, ventrikel, nod sinus, nod atrioventrikel (AV), dan berkas AV. Ciri-ciri bentuk gelombang isyarat elektrik yang tidak bergerak dan mempunyai pelbagai frekuensi membolehkan penggunaan Pengagihan Frekuensi Masa (TFD) dalam analisis.

Tujuan utama kajian ini adalah untuk membangunkan satu skema ketepatan tinggi untuk pengesanan CVD, termasuk iskemia dan aritmia, bagi bentuk gelombang isyarat ECG berselang panjang. Skema ini adalah berdasarkan analisis TFD bukan linear, yang disokong oleh kaedah pengambangan dan pengelas pembelajaran mesin, khususnya Mesin Vektor Sokongan (SVM). Selain daripada skema TFD yang baharu, penggunaan pelbagai petunjuk berbanding petunjuk tunggal dan selangan satu minit berbanding denyutan atau kerangka untuk pengelasan menyumbang kepada penambahbaikan prestasi pengesanan. Di samping pangkalan data MIT yang masyhur, alat ECG berkuasa rendah dengan 7 pentunjuk turut direka dan diguna pakai. Alat ECG ini diguna untuk memperoleh data mentah ECG bagi menilai skema cadangan untuk data ECG di luar pangkalan data ECG MIT dan membolehkan pengesanan CVD masa nyata. Data ECG yang dikumpul melalui alat ini juga dinilai untuk kes normal dan luar biasa. Skema cadangan ini memeriksa dan menilai pelbagai kes ECG normal dan luar biasa yang merangkumi penyakit kardiovaskular seperti aritmia dan iskemia. Set data yang diguna dalam kajian ini khususnya diambil daripada pangkalan data ECG MIT dan diguna pakai untuk latihan pengelasan dan penilaian prestasi.

Skema cadangan ini menyumbang kepada ketepatan, kepekaan, dan kekhususan menyeluruh yang tinggi melebihi 99% bagi pengesanan CVD. Keputusan pengesanan aritmia ialah 99.39% ketepatan, 99.38% kepekaan, dan 99.44% kekhususan. Manakala keputusan bagi pengesanan iskemia ialah 99.10% ketepatan, 99.09% kepekaan, and 99.13% kekhususan. Keputusan tersebut menunjukkan bahawa skema cadangan ini sesuai digunakan untuk mengesan penyakit kardiovaskular dan boleh dijadikan pelantar yang baik untuk sistem pengesanan CVD automatik dalam menyediakan pengawasan berdasarkan permintaan atau pengawasan berterusan untuk jangka masa yang lama pada ketepatan yang tinggi.

ACKNOWLEDGEMENTS

First and foremost, I would like to thank almighty ALLAH (S.W.T), the Most Beneficent and the Most Merciful for giving me the strength, courage, and his blessed guidance during my post graduate period.

I would like to thank my mother for her supportive prayers, calls, and blessings. I am also thankful to my brothers, friend and many others for their support.

I am thankful and grateful to my supervisor, Associate Professor Dr. Shaiful Jahari Bin Hashim for giving me the opportunity to embark on this research. His consistent motivation, support, and guidance have been very crucial in the completion of my research.

I would like to express my sincere gratitude to my supervisory committee members, Associate Professor Dr. Wan Azizun bt. Wan Adnan, Associate Professor Dr. Ahmad Fazli Abdul Aziz, and Dr. Fakhrul Zaman Bin Rokhani for their constructive suggestions during my research period and for dedicating their time in reviewing this thesis. Their valuable suggestions and comments have been very helpful in modifying the thesis.

I would like to express my sincere gratitude to Dr. Nasser G. Khaleel and ICU staff in Ibn-Al Nafees Hospital for all efforts and support during data gathering process.

I certify that a Thesis Examination Committee has met on 4 June 2018 to conduct the final examination of Ahmed Faeq Hussein on his thesis entitled "A Robust High Accuracy Cardiovascular Disease Detection System Based on ECG Energy Concentration Time-Frequency Analysis Supported by Threshold and Intelligent Classifier" in accordance with the Universities and University Colleges Act 1971 and the Constitution of the Universiti Putra Malaysia [P.U.(A) 106] 15 March 1998. The Committee recommends that the student be awarded the Doctor of Philosophy.

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LIST OF ABBREVIATIONS

ADC	Analog to Digital Converter
AF	Adaptive Filter
AM-FM	Amplitude Modulated – Frequency Modulated
ANN	Artificial Neural Network
ATT	Attribute Protocol
AWGN	Additive White Gaussian Noise
BJD	Born-Jordan Distribution
BLE	Bluetooth Low Energy
CAD	Coronary Artery Disease
CL	Chloride
CR	Compression Ratio
CSV	Comma-Separated Values
CVD	Cardiovascular Diseases
CWD	Choi-Williams Distribution
DAGSVM	Directed Acyclic Graph SVM
DCT	Discrete Cosine Transform
DTCWT	Dual Tree Continuous Wavelet Transform
ECG	Electrocardiogram
FFT	Fast Fourier Transform
FIR	Finite Impulse Response
FN	False Negative
FP	False Positive
FPR	False Positive Rate
GAP	Generic Access Profile

GATT	Generic Attribute Profile
HPF	High Pass Filter
HR	HR Heart Rate
HRV	HRV Heart Rate Variability
I, II, III	Limb Leads
IA	Instrumentation Amplifier
IF	Intermediate Frequency
K	Potassium
KNN	K-Nearest Neighbors
L2CAP	Logical Link Control And Adaptation Protocol
LA	Left Arm
LBBB	Left Bundle Branch Block
LFM	Linear Frequency Modulated
LL	Left Leg
MF	Median Filter
MI	Myocardial Infarction
MSE	Mean Square Error
OAA	One-Against-All SVM
OAO	One-Against-One SVM
PAC	Premature Atrial Contractions
PRD	Percent Root Mean Square Difference
PVC	Premature Ventricular Contractions
PWVD	pseudo Wigner-Ville Distribution
RA	Right Arm
RBBB	Right Bundle Branch Block

RLD	Right Leg Driver
ROC	Receiver Operating Characteristic
SAS	Statistical Analysis System
SHD	Structural Heart Diseases
SD	Spectral Delay
SMP	Security Manager Protocol
SNR	Signal to Noise Ratio
SoC	System On Chip
SVM	Support Vector Machine
TFD	Time-Frequency Distributions
TN	True Negative
TP	True Positive
TPR	True Positive Rate
UART	Universal Asynchronous Receiver-Transmitter
V1,V2, … V6	Chest Lead
WAF	Wavelet Adaptive Filter
WBANs	Wireless Body Area Networks
WCOH	Wavelet Coherence
WCS	Wavelet Cross Spectrum
WSNs	Wireless Sensor Networks
WT	Wavelet Transform
WVD	Wigner-Ville Distribution
XWT	Cross Wavelet Transform

CHAPTER 1

INTRODUCTION

1.1 Overview

Electrocardiogram (ECG) is a non-invasive method that is used as an interpretation tool for detecting heart diseases or cardiovascular diseases (CVD). ECG signal is commonly used as a fundamental scheme for the detection and diagnosis of CVD. ECG is the record of potential bioelectric variation with respect to time as the heart beats. It offers valuable information about the heart functional aspects and cardiovascular system as well. The ECG signals can vary from one to another due to the differences in the size of the human's body anatomy. This can vary based on sex, age, body weight, heart location and chest dimension. As the ECG signal is the most commonly acquired non-invasive signal for the patient checking and monitoring process, it is important to have a highly accurate CVD problems detection based on ECG signal analysis. ECG recording can be achieved with the aid of surface electrodes (ECG sensors) on the limbs or chest. These electrodes sense the weak electrical ECG signals and transfer them to ECG device [1, 2].

In the medical evaluation, the CVD detection is based on the alteration in ECG signals that acquired during the test. The normal heartbeat in a regular rhythm will show the line tracing of the P, QRS, and T waves look normal. If there is any obvious changes in the line tracing of the P, QRS, T, thus the heart may have problems. Comparison of overall ECG signal pattern and shape allows doctors or physicians to identify various types of CVD [3].

The heart abnormality problems mainly divided into two types, namely arrhythmia and ischemia. Arrhythmia refers to any change from the regular electrical impulses sequence. The electrical impulses may be too slow, too fast, or erratically that can cause the heart to beat too fast, too slow, or erratically. When the heart does not beat correctly, it cannot pump blood effectively. When the heart could not pump blood efficiently, the lungs, brain and all other organs cannot work appropriately and may shut down or damage. On the other hand, Ischemia is a type of CVD that caused by narrowed arteries of the heart. When arteries are narrowed, the blood flows will be reduced and less oxygen supplies the heart muscle. This is also identified as coronary artery heart disease and can eventually lead to heart attack [4-6].

To accurately characterise cardiovascular disease, a precise and reliable ECG waveform acquiring procedure is necessary. The ECG analysis procedure based on extracting the required features (information and characteristic) components from the ECG signal. The features are adequately representative of the physical heart situation and the heart disease problem. The non-stationary and multi-frequency components behaviour of biomedical signal activities makes the use of time-frequency distributions (TFDs) for analysis inevitable [7]. The time-frequency (TF) analysis provides simultaneous interpretations in both time and frequency domains enabling comprehensive presentation, explanation and interpretation of electrocardiogram (ECG) signals [8].

The nature of ECG signals are whereby the transitory disease signs may appear arbitrarily on the time domain scale. Hence, the method to diagnose the abnormality by individual beat or frame (number of few beats) is difficult, time-consuming and disposed to human errors. An alternative is to use computational techniques for automatic heart disease diagnosis. An automatic system of heart disease classification from acquired ECG signals can be divided into four steps as follows: (1) ECG signal pre-processing; (2) ECG signal segmentation; (3) feature extraction; and (4) classification process. In each of the four steps, a valid action is taken and the final objective is the heart disease identification [9].

Automated and robust ECG CVD classification and detection technique is the use of artificial intelligence, pattern recognition algorithms, and knowledge bases to figure out automatically the CVD of traced ECG that obtained usually from a patient [10]. Where the robust algorithm can perform a wide range of datasets solutions without need to resetting its parameters. Many researchers have reported automated or semi-automated classification and detection of CVD based on the features extracted from ECG signals. However, most of them use a single beat or frame (few beats) as a base to extract the related features. This selection of using only a few limited beats may be useful to aid the expert physician or cardiologist. Unfortunately, it is very limited to provide an accurate interpretation to the screening by the general practitioners (GP) at the hospitals or out-of-hospital self-checking with wearable ECG devices [11]. Besides, mobile health (mHealth) devices assessments can be used as clinical decision support tools at the point-of-care that can decrease the treatment time and improve the long-term outcomes among patients with rheumatic and structural heart diseases (SHD) [12, 13].

1.2 Problem Statements

In analysing the CVDs, the required disease components should be extracted as features from the ECG signal. The ECG signal waveforms properties are related to both ventricular bases and atria, and they represent the heart and cardiovascular system conditions. As the nature of ECG signal waveforms characteristics are both multi-component and non-stationary, spectral components of various ventricular and atria based signals are overlapped with each other. The usage of traditional time-based analysis method, therefore, can provide an unacceptable error rate during the CVD episodes. Moreover, atria based signal waveforms are narrower thus challenging to track and observe it. The joint TFDs are used in these cases in order to improve CVD detection accuracy by analysing the overlapping signal components and thus better in isolating and differentiating the CVDs activities. To make matter worst, the ECG signal is also non-stationary with non-linear characteristics. Unfortunately, most of the existing techniques employed for ECG are based CVD detection mainly used linear techniques [9, 14].

The main research problems to be addressed in this thesis as follow:

i. The clinical ECG devices with 12-lead are normally large, heavy and expensive and they are only available in hospitals. Moreover, it cannot provide a raw data by itself unless it is connected by expensive hospital or clinic network and provide just a paper based printed ECG results. Holter monitor can be used out-of-hospital to record extended duration of ECG (for examples 24 hours) but only after the CVD is confirmed upon patients with approved prescription from cardiologist. They are not suitable for screening purposes. There is a gap for out-of-hospital ECG based devices, for screening CVDs [15-18]. A range of handheld devices produce diagnostic quality lead I or single-lead ECGs [11, 19]. Besides, commercial ECG devices that used in hospitals and clinics These results are printout by using a thermal printer which is a non-permanent printing and can be erased after few months [20, 21].
ii. The using of TFDs for analysing ECG is necessary according to the ECG signal nature which is multi-component and non-stationary characteristics [22, 23]. In addition, The fact that the ECG signal itself can characterize hundreds of CVDs [24]. However, the optimised selection of TFD that can give a better interpretation still represents a challenge, where there is no fixed criteria to evaluate TFDs to analyse ECG signal.
iii. The CVD contains two main categories namely arrhythmia and ischemia. However, the CVD patient may have either arrhythmia or ischemia, and a causal relation between arrhythmia and ischemia may be presented in some patients [25]. Most researches focused and developed the analysing method for only a single CVD type independently either arrhythmia or ischemia artefact. This will lead to much reduced overall accuracy where the potential patient might have various types of CVD and not properly or comprehensively tested [26-28]. Furthermore, the connection or the overlapped between arrhythmia and ischemia is not clearly established but this may be due to the lack of accurate detection methods [26, 29].
iv. In CVD detection, the minimum acceptable arbitrary analysis duration is 30 seconds [17]. But, to the best of author knowledge, the longer analysis intervals such as 30 seconds or one minute and longer duration are not being considered. The longer period analysis is crucial for providing high accuracy for interpretation process [11, 30].

1.3 Motivation

According World Health Organization (WHO) report, the Heart and CVDs are the number one or the first cause of death globally where more people die annually from heart and cardiovascular diseases than from any other cause. An estimated 17.7 million death caused by heart disease in 2015, representing 31% of all global deaths. The WHO mortality projections from 2004 to 2030 that were designed with equivalent approaches to those applied in the inventive global burden of disease study state that the CVD death for aging are expected to increase to 23.3 million in 2030. In Malaysia, the heart diseases caused death to 36% of all deaths in 2014 which represent the number one or the first cause of death [31, 32]. The mortality is only part of the problem because most the patients who survived from CVDs problems, for example heart attack or myocardial infarction, will probably experience complication and becomes disable for the rest of their life. Extra care and cost are need for their living and recovery.

Many factors make the CVDs being the most mortal disease around the world. More than 75% of heart diseases deaths occur in low-income and middle-income countries where the treatment of this disease is at a very high cost comparative to their cost of living [33-35]. The American Heart Association (AHA) reports that the heart attacks treatment cost ($207.3 billion) were two of the ten most expensive hospital principal discharge diagnoses in 2016 [36]. Moreover, many potential heart patients have no prior symptoms (asymptomatic) to identify the heart problem such as silent ischemia, paroxysmal atrial fibrillation, and Brugada syndrome cases [37-39].

As the world population ages, massive pressure is being placed on the medical health care delivery system to improve the quality of care services while dropping overall costs. The existing quality of clinical care can only be improved when the health care system becomes expressively more efficient. One way to decrease health services costs while keeping quality of care that is to make available systems that monitor an individual as they go around their everyday activities as well as reducing the required doctor's visits times. Physicians can customise these systems to screen individuals recovering from a present cardiac condition, those at risk, and those facing cardiac discomfort. The home based or out-of-hospitals monitoring for individual over extended periods of time can be useful to help a physician to track disease progression. Earlier disease state detection can then lead to earlier intervention and treatment. Moreover, to monitoring disease progression, physiological monitoring on everyday basis can help establish normal physiology for an individual and can offer comment for more targeted treatments.

The ambulatory or one channel portable ECG monitoring device has established its rule particularly as an indicator for infrequent episodes and therapeutic control [40]. The accessibility of high-performance low-cost computing technology contributes to the improvements of ECG detection techniques by providing a reliable solution for an accurate and intelligent interpretation. The rising cost of health care will make admission of patient to the hospitals unnecessary without a screening results confirmation. A new design for portable ECG device for high accuracy CVD detection will assist in making the potential patient to be less hospital dependent.

1.4 Objectives

This project aims to develop a multi-leads robust CVD detection scheme. The basic concept of this development is based on using TFDs supported by intelligent classifier. This scheme can be achieved in effective way to satisfy the following:

i. To design and implement a wearable, wireless ECG device sensor for continuous monitoring that used to acquire ECG signals. The proposed device has the ability to capture multi-leads ECG signal and save it in to individual files.
ii. To develop a robust high accuracy out-of-hospital CVD detection scheme by employing joint time-frequency (TF) related ECG features with new definition of interpretation interval that is satisfy the clinical requirements. This scheme is optimization to use a single algorithm for analysing both CVDs arrhythmia and ischemia by using joint time-frequency distribution (TFD) that is supported by intelligent classifier.
iii. To validate the proposed CVD detection scheme in terms of accuracy, sensitivity and specificity.

Table 1.1 illustrates the contribution matrix of this study with respect to other works.

Table 1.1 : Contribution matrix of proposed work

Contribution Features	Proposed Work	Other Works
ECG data from high mobility device	✓	×
High accuracy, sensitivity and specificity (>99%) for both arrhythmia and ischemia detection	✓	×
Use 1-minute ECG quantum with continuous sequence of beats instead of beat based	✓	×
Related TF features	✓	✓
TFD in analysis	✓	✓
Automated feature extractions and classifications	✓	✓
Multi-lead	✓	✓

1.5 Scope of the study

In this study, the robust CVD detection system is proposed and evaluated as following:

i. The system involve the designing and implementation of out of hospital handheld wearable ECG acquiring device that used by normal consumer for heart monitoring.
ii. The screening of both CVDs (arrhythmia and ischemia) which can prevent the further complications and save the efforts and resources that can be used in another development.
iii. Using of ECG datasets combinations to cover the CVDs cases, where two main datasets are employed in this study. First the MIT-Physionet datasets and second the collected datasets that gathered from normal individuals and ischemic patients from Ibn Al-Naffees Hospital for Cardiac Diseases in Baghdad, Iraq.
iv. Analysing long ECG segments (interval) at a multi-lead capability instead of using a single lead interpretation.
v. The using of ECG extracted features that denoted by QRS, ST and PR components to analyse type of CVDs.
vi. The using of pattern recognition classifier to support the automation process.

1.6 Thesis layout

This thesis is arranged in such a way that it affords a continuous and smooth information flow to the reader, regarding the development and analysis of the heart disease detection system. There is a total of five main chapters that are subdivided into suitable sections. The main five chapters in this thesis are Introduction, Literature Review, Research Methodology, Results and Discussions, and finally Conclusions and Recommendation of the study. The content of each chapter is outlined as follow:

Chapter 2 demonstrates the literature review and the methodologies of the previous studies of ECG analysis using the various applications and algorithms of features extraction and classifier are reviewed as well. This chapter deals with the past and current trends of the ECG analysis study.

Chapter 3 will discuss the research methodology and system design of the project. This chapter explains how the project is organized and the flow of all the project operation part. This chapter discusses about the ECG acquiring signal device implementation and the design and implementation of analysis scheme algorithm that is based on Choi-Williams TFD and supported by SVM classifier.

Chapter 4 discusses the performance evaluation of proposed system. The ECG acquiring process evaluation, features extraction, and classification results of ECG analysis algorithm are discussed. All discussions that concentrate on the result and performance of the ECG signal gathering and analysing that gives a review the correlation of all methods.

Chapter 5 discusses the conclusion and further development of the study. This chapter also presents and describes the problems, limitations and the recommendation for this study and overall heart disease analysis for the future development or modification.

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