HARDWARE AND SOFTWARE DEVELOPMENT OF ECG BIOMETRIC SYSTEM

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UNIVERSITI SAINS MALAYSIA

2018

HARDWARE AND SOFTWARE DEVELOPMENT OF ECG BIOMETRIC SYSTEM

by

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Thesis submitted in partial fulfillment of the requirements for the degree of Bachelor of Engineering (Electronic Engineering)

JUNE 2018

ACKNOWLEDGEMENT

I would like to express my deepest and sincere thanks to my final year project supervisor, Assc. Prof. Dr.Dzati Athiar binti Ramli who had supported me throughout my project. Before starting to do my project, she provides me with a very clear concept on my project, so I can clearly know what I should do. Besides that, her guidance and advices are very important to me when I am facing problem. Furthermore, she willing to spend her precious time for me to discuss my project and correct the mistakes that I have done in my thesis. I can come out with a good thesis is very much appreciated.

Besides, I would like to express sincere gratitude thanks to my examiner, Mr. Ahmad Nazri Ali for his effort and time spending on my thesis and viva. He is also giving the positive feedbacks and comments on my project.

In addition, I am want thanks to my friends who willing to contribute their ECG signals as my samples for the database, this project will be never success without them. I most grateful to my partner Kong Chun Lei and Chen Kok Keat from School of Electric and Electronic Engineering for participate Innovate Malaysia Competition 2018 with me.

Last but not least, I am also thanks my family who give me the spirit support to complete my undergraduate studies.

Table of Contents

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ADC	Analog-to-Digital Converter
ANN	Artificial Neural Network
BPF	Bandpass Filter
CMRR	Common-Mode Rejection Ratio
ECG	Electrocardiogram
GUI	Graphical User Interface
HPF	High Pass Filter
IA	Instrumentation Amplifier
LA	Left Arm
LPF	Low Pass Filter
MLP	Multilayer Perceptron
Op-amp	Operational Amplifier
RL	Right Leg
RLD	Right Leg Drive
trainbfg	BFGS Quansi-Newton Backpropagation
traincgb	Conjugate Gradient with Powell/Beale Restarts
traincgf	Fletcher-Powell Conjugate Gradient
traincgp	Polak-Ribiére Conjugate Gradient
trainlm	Levenberg-Marquardt Backpropagation
trainscg	Scaled Conjugate Gradient
trainrp	Resilient Backpropagation
trainoss	One Step Secant

PERKEMBANGAN PERANGKAAN KERANGKA DAN PERISIAN SISTEM BIOMETRIK ELEKTROKARDIOGRAFI

ABSTRAK

Keselamatan adalah isu utama di dunia dan tidak ada yang benar-benar selamat. Sekarang biometrik telah menjadi alat keselamatan berguna dalam beberapa dekad kebelakangan ini kerana keberkesanannya dalam mengenal pasti dan mengesahkan pengguna yang dikehendaki berbanding penceroboh yang berpotensi. ECG telah dicadangkan sebagai biometriks yang menjanjikan untuk pengenalan dan pengesahan manusia. Kelebihan biometric ECG adalah sangat selamat, dan sulit berbanding dengan cap jari, iris, dan muka. Walau bagaimanapun, 12 bilangan petunjuk yang digunakan untuk mengumpul isyarat ECG dalam sistem pengenalan yang tipikal tidak berkesan. Oleh itu, projek ini mencadangkan kit pengesanan ECG mudah alih yang direka dengan menggunakan hanya oleh Lead 1 untuk pengesanan dan rakaman ECG. Aplikasi Android juga membantu untuk mengumpul isyarat ECG yang betul dengan memeriksa status subjek ECG dalam projek ini sebelum data ECG subjek direkodkan. Dalam projek ini, algoritma Pan-Tompkins digunakan sebagai teknik ekstraksi ciri titik fiducial ECG manakala rangkaian saraf buatan digunakan untuk sistem pengenalan. Penilaian prestasi menunjukkan bahawa 93.65% daripada keseluruhan prestasi sistem dan 85% ketepatan mata pelajaran individu berdasarkan 10 data latihan mata pelajaran yang berlainan dan 20 ujian subjek yang berlainan. Hasil eksperimen ini menjanjikan dengan itu isyarat ECG terbukti menjadi modaliti yang berdaya maju untuk sistem biometrik.

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ABSTRACT

Security is a top issue in the world and nothing is completely secure. Now biometrics has been a useful security tool in recent decades because of its effectiveness in identifying and authenticating desired users versus potential intruder. ECG has been proposed as promising biometrics for human identification and authentication. The advantage of ECG biometric is highly secure, and confidential compared to fingerprint, iris, and face. However, 12 number of leads used to collect ECG signal in typical identification system is not efficient. So that, this project proposes a portable ECG detection kit that is designed by using solely by Lead 1 for ECG detection and recording. The Android application also helps to collect proper ECG signal by checking the status of subject's ECG in this project before the subject's ECG data is recorded. In this project, Pan-Tompkins algorithm is used as feature extraction technique of ECG fiducial points while artificial neural network is used for identification system. The performance evaluation shows that 93.65% of overall system performance and 85% of individual subject accuracy based on 10 different subject's training data and 20 different subject's testing. This experimental result is promising hence ECG signal is proved to be a viable modality for biometric system.

CHAPTER 1

INTRODUCTION

1.1 Background

Biometrics is science of identifying and verifying individual based on his or her physiological and behavioral biometric traits. Physiological traits are face, palmprint, vein and iris while behavioral traits are keystroke dynamics, gait analysis, voice ID, mouse use characteristics, signature analysis and cognitive biometrics.

Traditional security system based on password, key and smart card are now outdated because they can be stolen and copied. Now biometrics has been a useful security tool in recent decades because of its effectiveness in identifying and authenticating desired users versus potential intruder.

There are several biometric methods are based on physiological traits of humans, which can be categorized into exterior and interior. Interior group includes ECG signal and exterior group includes fingerprint [1], face [2]and iris or retina [3]. While the exterior biometric has been researched and show that they have significant disadvantages because they are easy for attackers to access, and they are not robust against copy or spoof [4]. In this project, the interior ECG biometric signal will be used to perform biometric identification security system which is more secure compared to exterior biometric.

The use of ECG for identity recognition dates to the pioneer studies of Kyoso & Uchiyama [5] and Biel et al. [6] which revealed that ECG contains sufficiently detailed information to identify an individual uniquely. 1-lead ECG for identity verification had researched by T.W. Shen et al [7]. Their research shows that the ECG is a potential biometric for human identity verification. Report of discrete wavelet transform applied on personal identity verification show that ECG used as a biometric measure for personal identity verification is feasible [8]. Nowadays, ECG biometric systems only required an ECG smart band to extract the ECG signal feature as personal identification in system matching or authentication.

1.2 Problem Statement

A typical architecture of ECG signal acquisition consists 12-lead ECG gives a tracing from 12 different “electrical positions” of the heart as shown in Figure 1.1. The ECG leads are grouped into two different electrical planes which are pre-cordial leads and frontal leads. The pre-cordial (V1-V6) view the heart from a horizontal plane while frontal leads (Lead I-III, aVR,aVF, and aVL) view the heart from a vertical plane. This is a problem for a user to install 12 electrodes to collect all the ECG lead signals for an identification system. Practically, for implementation of ECG signal detection, the architecture required placement of electrodes and the design has to be portable. Due to this requirement, a simple architecture of ECG detection kit is designed by using Lead I ECG signal, i.e. left arm(LA) and right arm(RA) as ECG signal sources and right leg(RL) improving the common-mode rejection of system. The collected ECG signal is then extracted using Pan-Tompkins and an ANN is used as a classifier for ECG biometric identification system.

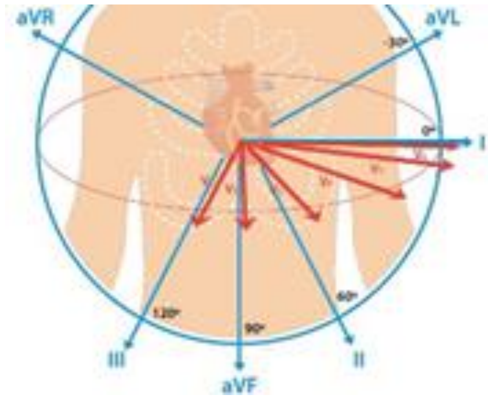


Figure 1.1: 12 ECG lead placements

1.3 Objective

The main objectives of this project are:

1. To build a portable hardware of electrocardiogram (ECG) detection kit which is able to record ECG data of subject based on Lead I.
2. To develop an ECG biometric identification system based on fiducial points of ECG signal for feature extraction method and artificial neural network(ANN) as classifier.
3. To evaluate the performance of the developed system and create the graphical user interface(GUI)

1.4 Scope of Project

For this project, the ECG detection as the biometric trait is only specially targeted to human beings as to purpose solution for the problem statement. The system is involved the hardware design of ECG detection kit, and the software design of Android application, and ECG biometric identification system.

For the ECG detection kit, it is designed to be portable. The size of the ECG detection kit needs to be small, so it is portable. The ECG detection kit needs to get the desired

ECG signal from the wrist of user and its frequency is in the range of 5Hz to 40Hz. The signal is saved into SD card.

For the Android application, an application is developed and named “ECG Plot”. The application responsibility is used to check the status of user’s ECG in this project before the subject’s ECG data is recorded. This Android application is programmed for version 4.3 of Android OS and above.

Besides that, an ECG biometric identification system is developed. Pan-Tompkins algorithm is used to find out the fiducial points of ECG signal. The fiducial feature will be used as the input variable of artificial neural network while the artificial neural network is executed as the matching classifier in the ECG biometric identification system. The result of classification from neural network will identify the subject of ECG training data. There is the limitation for this system which is the number of different subject’s training data should be less than 15, the subject’s ECG should be detected and recorded under rest mode or optimal condition and there are 3 leads are used.

1.5 Thesis Outlines

The thesis is divided into five chapters. In chapter 1, the introduction which gives reader know about the overview of ECG biometrics. It explains the motivation which leads are used for development of ECG detection kit and ECG biometric identification system. The problem statement, objective, scope of work and thesis outline is also in this chapter.

In chapter 2, the literature review discusses the basic knowledge and understanding about electrocardiogram (ECG). The design of similar research area is also described and compare in this chapter.

In chapter 3, the methodology is discussed. The working principle of purpose system is explained. The implementation of the hardware and the software are explained in detail.

The result and discussion of the developed system are analysed and presented in chapter 4. The performance evaluation of system is also discussed in this chapter.

Lastly, chapter 5 is concluding the summarizes the implemented project. The number of completed achievement for the objective is presented and there are some recommendations for future improvement of this project.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter presents the review to gain the ideas plus concept to help in research stage from the previous project. Section 2.2 explains the fundamental of electrocardiogram (ECG). Section 2.3 discusses the placement of electrode and the number of electrodes. Section 2.4 discusses fiducial points of ECG signal as the biometric traits. Next, section 2.5 presents the overview of the previous project of portable hardware of ECG detection kit. Section 2.6 discusses Pan-Tompkins algorithms for feature extraction based on fiducial points of ECG signal. Section 2.7 explains the fundamental of artificial neural network(ANN). Finally, the summary of the literature review is in section.

2.2 The Electrocardiogram (ECG)

An electrocardiogram is a recording of the electrical activity of heart muscle by electrodes. Heart rhythm and cardiac cycle normally studied in the healthcare. A normal ECG waveform as shown in Figure 2.1.

ECG consists of three primary features which are P wave, QRS complex and T wave. The first electrical signal on a normal ECG originates from the atria and is P wave. There is a short physiological delay as the atrioventricular node has slowed the electrical depolarization before it proceeds to the ventricles. Next, a short delay where no electrical activity is seen on the ECG called PR interval, it is represented by a straight horizontal or called ‘isoelectric’ line and then follow by QRS complex. The QRS complex is represents the depolarization of the ventricles and the strongest wave in an ECG. The QRS complex is first the downward deflection (Q wave) and then followed by upward deflection (R wave) and last is the next deflection downward (S wave). In the case of the ventricles, there is also an electrical signal reflecting repolarization of the myocardium. This is shown in the ST segment and the T wave. The ST segment is normally straight horizontal, and the T wave in most leads is an upright deflection of variable amplitude and duration.

For digital signal processing, ECG bandwidth need to fulfil the certain requirement. For non-diagnostic ECG, bandwidth must at least between 5Hz and 40Hz. For non-diagnostic ECG, bandwidth must at least between 0.05Hz and 150Hz. [9]

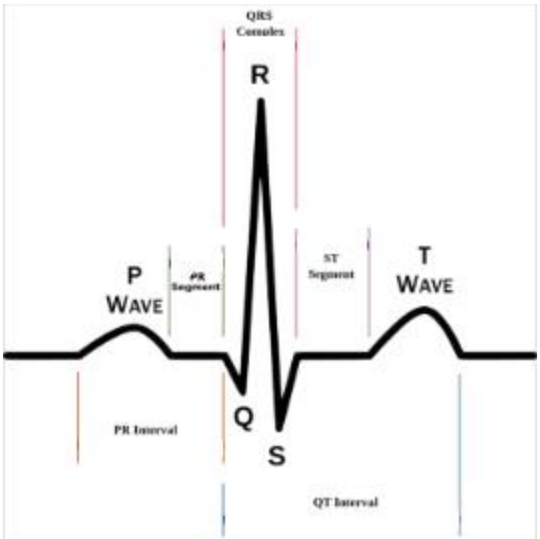


Figure 2.1: A normal ECG waveform

2.3 ECG electrode placement and effect of the number of electrodes

A lead is a view of the electrical activity of the heart from an angle across the body. The ECG leads are grouped into two different electrical planes which are pre-cordial leads and frontal leads. 12 ECG Leads placement is shown in Figure 2.2

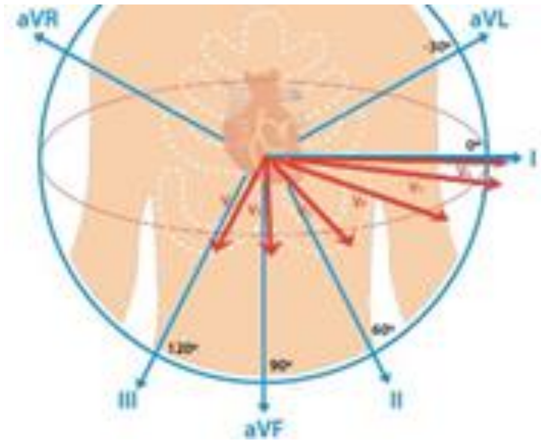


Figure 2.2: 12 ECG Leads placement

For frontal leads, Leads I, II, and III require a bipolarity which is a positive and a negative electrode for monitoring Next, the augmented leads— Augmented Vector Right (aVR), Augmented Vector Left (aVL), and Augmented vector foot (aVF) are unipolar and they require only a positive electrode for monitoring. For pre-cordial leads are unipolar and requires only one positive electrode. At the centre of the heart, the negative pole of all six leads is found. For frontal ECG leads, electrodes normally placed on Right Arm(RA), Left Arm(LA), and then Left Leg (LL), optional for Right Leg(RL) as a reference. The electrode placement site form Einthoven's triangle as shown in Figure 2.3. The lead is the different the voltage potential between positive and negative electrode sites. There are six frontal leads are derived from the Einthoven's triangle.

Lead I — The axis goes from shoulder to shoulder with the positive electrode placed on the left shoulder while the negative electrode placed on the right shoulder. The results in a 0-degree angle of orientation.

Lead II — The axis goes from the left leg to the right arm with the positive electrode on the left leg and the negative one on the right arm. The results in a positive 60-degree angle of orientation.

Lead III — The axis goes from right or left leg to the right arm with the positive electrode on the left or right leg and the negative one on the right arm. The results in a positive 120-degree angle of orientation.

aVR — The augmented unipolar right arm lead faces the heart from the right side. It is usually orientated to the cavity of the heart. All the deflections of P, QRS, and T are normally negative in this lead.

aVL — The augmented unipolar left arm lead faces the heart from the left side. It is orientated to the anterolateral surface of the left ventricle.

aVF — The augmented unipolar left leg lead. It is orientated to the inferior surface of the heart Precordial Chest Leads.

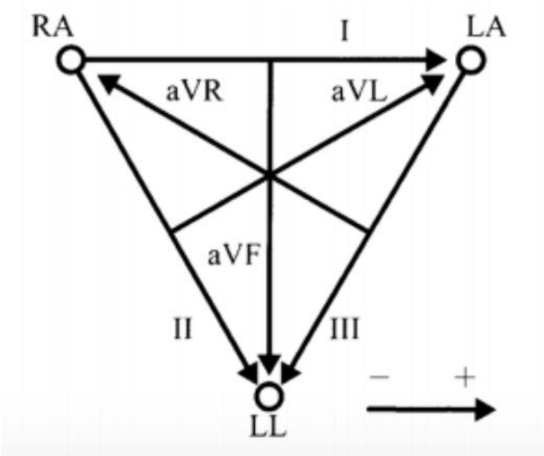


Figure 2.3: Graphical representation of Einthoven's triangle [28].

The equation below is all the equations of Einthoven's triangle.

$$I=LA-RA \quad (2.1)$$

$$II=LL-RA \quad (2.2)$$

$$III=LL-LA \quad (2.3)$$

$$aVF = LL - \frac{1}{2}(LA + RA) \tag{2.4}$$

$$aVL = LA - \frac{1}{2}(RA + LL) \tag{2.5}$$

$$aVR = RA - \frac{1}{2}(LA + LL) \tag{2.6}$$

For pre-cordial leads, the electrodes are placed at the chest as shown in Figure 2.4. The six chest electrodes:

V1 - placed in the fourth intercostal space, the right of the sternum

V2 - placed in the fourth intercostal space, the left of the sternum

V3 - placed between the position of V2 and V4

V4 - placed fifth intercostal space in the nipple line.

V5 - placed between the position of V2 V4 and V6

V6 - placed in the midaxillary line that is the same height as V4

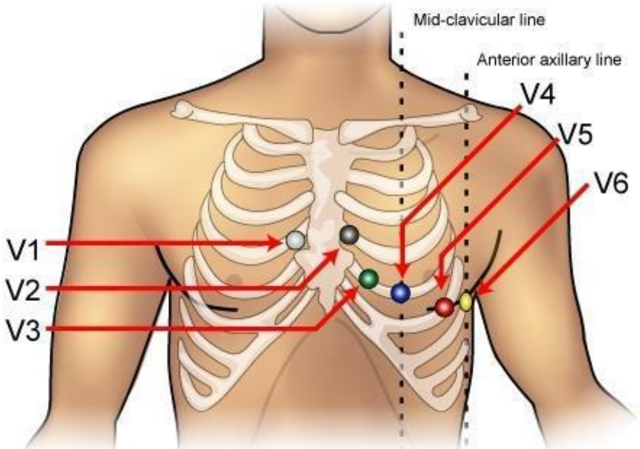


Figure 2.4: Pre-cordial ECG leads placement[29].

The electrode placement that not on standard electrode positions, for the acquisition of the 12-lead ECG, will cause differences in ECG signals and their interpretation [10]. It has also been shown that misplacement of electrodes employed by a reduced-lead set has effects on synthesized 12-lead ECGs [11].

The number of electrodes also has its role in ECG detection. The 3 electrode ECG lead is the most commonly used ECG in pre-hospital care and is most regularly utilized in continuous monitoring of the person who has had some form of cardiac event. There are two electrodes are required to take a single ECG lead only. The third electrode is for the reference point and its uses to set the body of common potential. The measurement of ECG with the third electrode will get better ECG.

2.4 Fiducial points of ECG signal as the biometric trait

For ECG biometrics system, the fiducial and non-fiducial approach of feature extraction has been studied for people verification and identification. The fiducial approach requires the detection of fiducial points from ECG signal. These ECG fiducial points can be the fiducial features represent the temporal and amplitude distances between fiducial point. On the other hand, non-fiducial approaches usually operate in the frequency domain, example for, wavelet discrete cosine transform.

In 2012, Tantawi, Manal M. et al. [12] presented that using fiducial based information such as characteristic peaks can have satisfied accuracy in ECG Biometric system. In 2016, Zeeshan Hassan et al. [13] presented that for small data sets will get a very high efficiency has been obtained by using fiducial techniques of feature extraction while non-fiducial techniques have high efficiency for a large population.

2.5 ECG detection device

An ECG detection system which presented by the previous works [14-18] have same circuit design structure. All previous works have ECG sensing and processing part and ECG converting and monitoring system part. ECG sensing and processing part consists of electrodes, instrument amplifier, noise filter. ECG converter and transmit system part consist of transmitter and storage. All the previous assessments have the common characteristic which is portable, and they are using reusable electrodes for sensing ECG signal. The previous assessments are converting the analog signal to digital data by an analog-to-digital converter(ADC) because digital data is easier to store compared to an analog signal.

A mobile electrocardiogram monitoring system is designed by A. Romero et al. [14] and it is shown in Figure 2.5. The ECG acquisition module is a three-lead ECG device, and consists of Front-End Amplifier (FEA) circuit, Analog-to-Digital Converter (ADC), microprocessor, Driven Right Leg circuit (DRL), and wireless transmission circuit, as shown in Figure 2.6. Here, FEA circuit, which contains a pre-amplifier and a band-pass filter, was designed to amplify and filter ECG signal. The gain of FEA circuit was set to about 112 times with frequency band of 0.05−150 Hz. Since this is a wearable device, so it is designed to have a rechargeable battery.

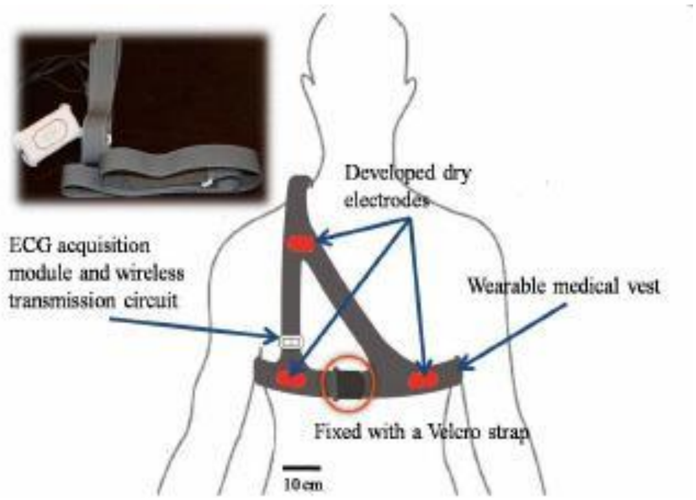


Figure 2.5: A Mobile Electrocardiogram measurement device [16]

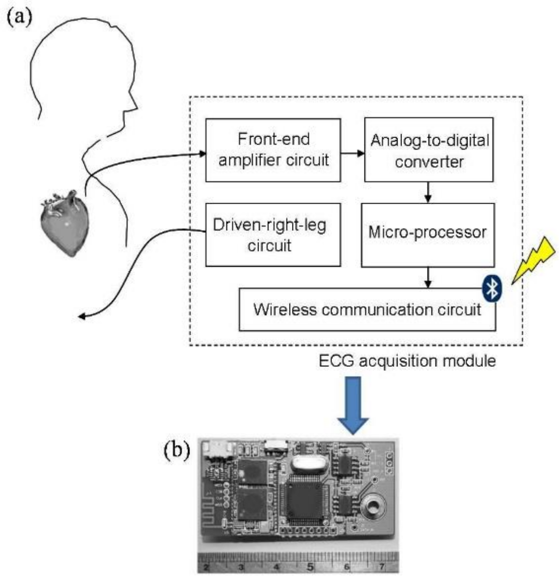


Figure 2.6: (a) Block diagram of module and (b) photograph ECG acquisition module [16]

Due to the surface is covered with AgCl to help for electric conduction, which may cause user to feel uncomfortable and it is not suitable for wear over a long time. A wearable conduction belt is designed by Sung-Yuan Ko et al [17], reusable ECG electrodes are used to measure the ECG signal. The measured result is like the traditional method.

Figure 2.7: The wearable conduction belt. [17]

2.5.1 ECG Sensing and Processing Signal Part

The heart electric signal has a very small amplitude (around 1mV) the goal is to digitize the ECG signal that the frequencies of the heart signal goes from the range of 0.05Hz to 100Hz. The first step is minimized frequencies out of that range must be and then they should pass through an amplification. Next, the signal must be manipulated so it can be in the range of 0-5V to be digitized. [14]

2.5.1 (a) Instrumentation Amplifier

Since ECG is just around 1mV is a differential measurement between two electrodes, an amplifier with very high gain is needed. The noise will be a serious issue for measure signal because signal-to-noise ratio(SNR) will be very small. So, electrodes require very high impedance presented by an instrumentation amplifier because the characteristics of the biopotential electrodes have a big problem with the distortion of the signal. Instrumentation amplifier needs to have a high level of noise rejection. [14-18]. The circuit of the instrumentation amplifier is shown in Figure 2.8.

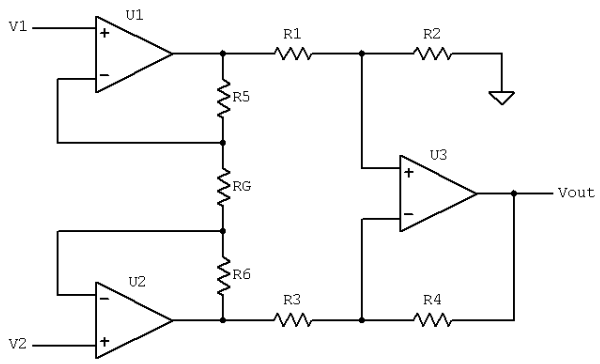


Figure 2.8: Instrumentation amplifier

2.5.1 (b) Bandpass Filter

A bandpass filter that ensures that the signal contains only frequencies from a range of frequency. The signal that out of range frequency will be filtered. [14-18]. The circuit of the bandpass filter is shown in Figure 2.9.

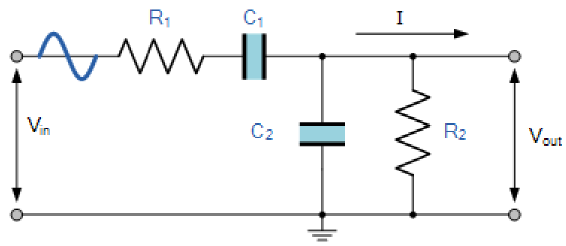


Figure 2.9: Bandpass Filter [30]

2.5.1 (c) Right leg drive circuit

A right leg drive circuit is an electric circuit that is installed to biological signal amplifier to reduce common-mode interference. The ECG circuit will get the better ECG signal without many external noises [14-18]. The circuit of the right leg drive is shown in Figure 2.10.

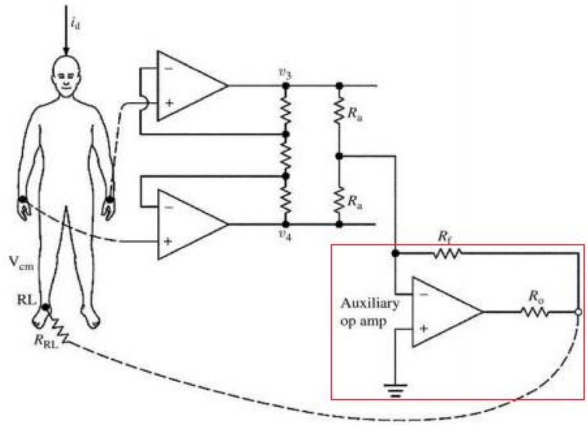


Figure 2.10: Right Leg Drive Circuit is the circled by red rectangular

2.5.2 ECG converter system

In previous assessments [14], the ECG converter system is used to convert the ECG signal which is in analog form to digital form so that it can be used for next processing(software). ECG converter and transmit system part consist analog-to-digital converter and ECG transmitter of Arduino board. The measured ECG signal is in the analog signal form. Two important parameters involve in this process. i.e. sampling rate, f_s which to define the number of samples taken in a second and sampling precision, N where to define number of different quantization levels for the sampling process. After that, it will save in SD card of Arduino.

2.6 Pan-Tompkins algorithm for find out ECG fiducial points

There are many types of algorithms to feature extraction of ECG fiducial points of a heartbeat. One of the studied algorithm of feature extraction of ECG fiducial points is Pan-Tompkins algorithm.

Pan Tompkins is one of the methods for the detection of ECG waves. The QRS detection algorithm introduced by Pan and Tompkins is the most widely used and often cited algorithm for the extraction of QRS complexes from electrocardiograms.

First, the signal passes through a digital bandpass filter composed of cascaded high-pass and lowpass filters to attenuate noise from the ECG signal. At derivative stage, the ECG signal is differentiation and the information of QRS slope is obtained. The ECG signal is squaring and then moving window integration. The squaring process intensifies the slope of the frequency response curve of the derivative and it helps to restrict false positives caused by T waves with higher than normal spectral energies. The moving window integrator produces a signal that consists the information of both the width and the slope of the QRS complex. The signal after process will have a delay compare to original signal because of delay by the total processing time of the detection algorithm. [19]. When QRS is obtained then P-point and T-point can be found.

2.7 Artificial Neural Network (ANN)

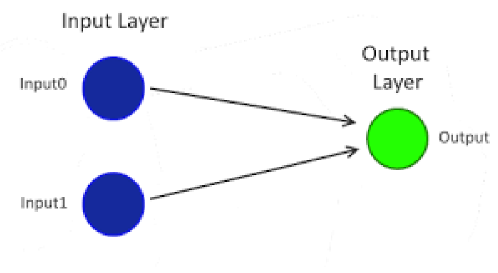
Artificial Neural Networks are relatively crude electronic models based on the neural structure of the brain. The brain basically learns from experience. This brain modelling also promises a less technical way to develop machine solutions.

2.7.1 Neural Learning

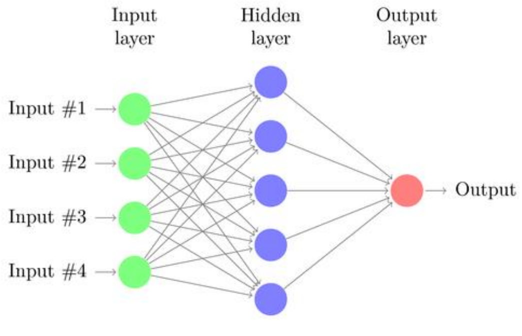
In ANN, learning can be referring to the methods of modifying the weights of connection links between the nodes of the specified network. Learning is the process of adapting random value parameters, weight, and bias of the neural network through a continuous process of simulation within the environment set. The learning algorithm defines how network weights are adjusted between successive training cycles or epochs. The most popular is the backpropagation learning algorithm of learning strategies of multi-layer perceptron(MLP).

2.7.2 Structure of Neural Network

There are two types of neural networks which are single layer perceptron network and multi-layer perceptron network. The single-layer perceptron network is the simplest neural network and consists of a single layer of inputs nodes and output nodes. The inputs are fed directly through series of weights to the outputs. The inputs and the sum of the products of the weights are calculated in every node. The difference between the structure of single-layers perceptron and multiple-layers perceptron is the multiple-layers perceptron consists of one or more hidden layers, the calculation of them will be different result. Multi-layer suitable for the complex condition. The structure of single-layer perceptron network and multi-layer perceptron network are shown in Figure 2.11.



(a)



(b)

Figure 2.11: (a) The structure of single-layer perceptron network; (b) The structure of multi-layer perceptron network

2.7.3 Feedforward neural networks (FNN) with backpropagation (BP)

Feedforward neural networks (FNN) is one of the Artificial Neural Network(ANN) wherein connections between the units do not form a cycle. Feedforward neural networks are the multi-layer perceptron model (MLP) and they have been widely used for many tasks like, pattern recognition, function approximation, and time series forecasting [20].

Back Propagation is the learning or training algorithm rather than the network itself. To train a network, it needs to give the output called the target for an input. The input and its corresponding target are called a training pair. Once the network is trained, it will provide the desired output for any of the input patterns [21]. The structure of feedforward neural networks (FNN) with backpropagation (BP) is shown in Figure 2.12

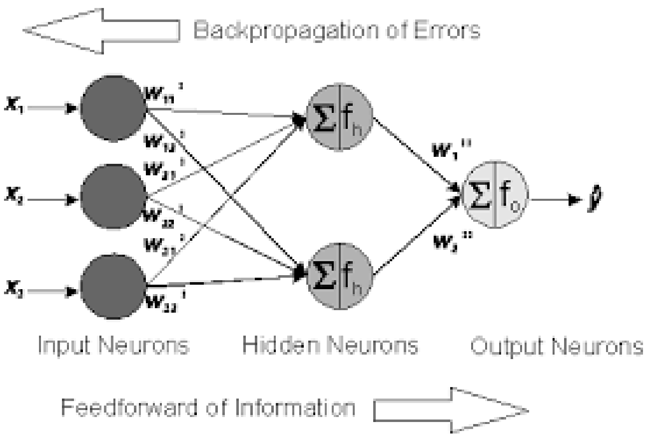


Figure 2.12: Feedforward neural network with backpropagation

2.7.4 Training and validation of Neural Network

The characteristic of a neural network system is its ability to learn through iterations. In the system, learning can be defined as the process of updating the internal representation of the system in response to external stimuli so that the performance of a specific task is improved. The learning algorithm defines how network weights are adjusted between successive training cycles or epochs. There are many learning algorithms of multi-layer perceptron model (MLP) and the most famous is the backpropagation learning algorithm, also called the generalized delta rule [22]. During the training process, the weights and the biases of neural network are adjusted to produce the desired output. This is done by calculating training errors, which are the difference between outputs and target, and then updates the weights and biases for every cycles or iteration. A flowchart of the complete training process for MLP neural network is shown in Figure 2.13.

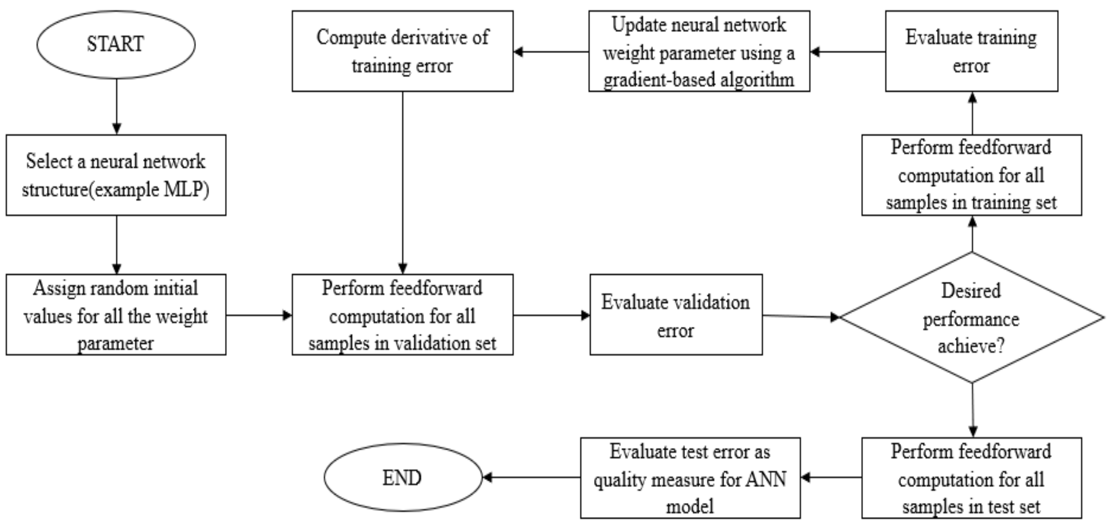


Figure 2.13: Flowchart of demonstrating neural network, neural model testing by using training data, validation data and test data which is sets in ANN modelling approach

The mean squared error (MSE) is evaluated on the entire training set. If the error decreases, the new vector of weights is accepted; otherwise, it is discarded. Hence, training may need to be performed several times before a good solution is found. As the weight vectors move closer to the correct orientation both the MSE may decreases.

2.7.5 Training Algorithms

The training algorithm is selected due to the complexity of the problem, the number of data points in the training set, the number of weights, the purpose of usage of training algorithms example pattern recognition function approximation.

There are many types of algorithms such as Levenberg-Marquardt Backpropagation (trainlm), BFGS Quasi-Newton Backpropagation (trainbfg), Resilient Backpropagation (trainrp), Scaled Conjugate Gradient (trainscg), Conjugate Gradient with Powell/Beale Restarts (traincgb), Fletcher-Powell Conjugate Gradient (traincgf), Polak-Ribiére Conjugate Gradient (traincgp), One Step Secant (trainoss), and Variable Learning Rate Backpropagation (traingdx).

According to previous researches [13,23-26], most of them are using Levenberg-Marquardt and Backpropagation (trainlm). According to one of the thesis ECG classification [23], Levenberg-Marquardt ANN convergence was much faster and accurate.

2.7.6 Levenberg-Marquardt backpropagation

Levenberg-Marquardt is one of the most popular tools for non-linear minimum mean squares problems. It is a suitable algorithm used in this ECG biometric system because the ECG signal has nonlinear dynamic behaviour. LM algorithm also approximates to the Gauss-Newton method and has been also used for ANN training. The Levenberg Marquardt algorithm was designed to approach second-order training speed without having to compute the Hessian matrix. When the performance function has the form of a sum of squares (as is typical 184 in training feedforward networks) then the Hessian matrix can be approximated as

$$H = J^T J \tag{2.7}$$

and the gradient can be computed as

$$g = J^T e \tag{2.8}$$

where J is the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases, and e is a vector of network errors.

The Jacobian matrix can be computed through a standard backpropagation method that is much less complex than computing the Hessian matrix. The Levenberg-Marquardt algorithm uses this approximation to the Hessian matrix in the following Newton-like update:

$$X_{k+1} = X_k - [J^T J + \mu I]^{-1} J^T e \tag{2.9}$$

The equation 2.9 represents Newton method. This is faster and more accurate with minimum error, using the approximate Hessian matrix. When μ is large, this becomes gradient descent with a small step size. Thus, μ is decreased after each successful step (reduction in performance function) and is increased only when a tentative step would increase the performance function. In this way, the performance function is always reduced at every iteration of the algorithm.

2.7.7 Finding Number of Hidden Neurons

Finding out the optimal number of hidden nodes for topology is the most difficult aspect of Artificial Neural Network (ANN) design. There are still no reliable ways to determine the number because it depends on many factors. If the number of neurons in the hidden layer is too less, the neural network may not be powerful enough and have low accuracy. If the number of neurons in the hidden layer is too many, it can cause very long training and recall time [22].

2.8 Summary

Conclusion, the fundamental of the electrocardiogram is studied in this chapter. In this chapter, there are many previously assessments with good and creative idea for portable ECG device. Pan-Tompkins algorithm can be used in feature extraction for input of neural network training. The ECG biometric identification system will use feedforward multilayer neural network (NN) with error backpropagation (BP) as classifier.

CHAPTER 3

METHODOLOGY

3.1 Introduction

This chapter presents the description of the software and hardware development of ECG biometric system and its working principle. Section 3.2 presentes the project implementation flow. Next, section 3.3 discusses the project requirement. Section 3.4 shows the overall project design and process modeling. Lastly, section 3.5 is the summary of methodology.

3.2 Project Implementation Flow

The project implementation consists of two parts which are hardware and software part.

The purpose of hardware part is to build a portable ECG detection kit that can detect and save the ECG signal from Lead I of the subjects. The procedure involves being in the following:

i) design a suitable circuit for ECG detection kit

ii) build the component circuit and test the circuit

The purpose of software part is developed an Android application and an ECG biometric identification system based on fiducial points of ECG signal using Artificial Neural Network. The procedure involves being in the following: