Analysis of Atrial Fibrillation Associated with Autonomic Nervous System Function in Stroke Patients Using Fuzzy Neural Network and Prediction Parameter

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หัวข้อวิจัย การวิเคราะห์ภาวะหัวใจห้องบนเต้นผิดปกติที่สัมพันธ์กับการทำงานของระบบประสาทอัตโนมัติในผู้ป่วยโรคหลอดเลือดสมองโดยใช้โครงข่ายประสาทเทียมแบบฟัซซีและพารามิเตอร์การทำนาย

ผู้ดำเนินการวิจัย นางสาวจามรี กลางคาร
นายยุทธนา พิมพ์ทองงาม
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หน่วยงาน คณะวิทยาศาสตร์และเทคโนโลยี
มหาวิทยาลัยสวนดุสิต

ปี พ.ศ. 2558

วัตถุประสงค์ของการศึกษาครั้งนี้คณะผู้วิจัยมุ่งเน้นสร้างความก้าวหน้าของวิธีในการวิเคราะห์ภาวะหัวใจห้องบนเต้นผิดปกติที่สัมพันธ์กับปัจจัยเสี่ยงต่อโรคหลอดเลือดสมองโดยใช้โครงข่ายประสาทเทียมแบบฟัซซี่และการประมวลผลสัญญาณ โดยขั้นตอนการทดลองเริ่มต้นจากเปรียบเทียบรูปแบบรูปแบบของคลื่นคลื่นไฟฟ้าหัวใจและรูปร่างของสัญญาณที่ช่วยแพทย์ในการวินิจฉัยโรคปัจจุบันได้มีการใช้คอมพิวเตอร์ไปใช้วิเคราะห์สัญญาณคลื่นไฟฟ้าหัวใจของผู้ป่วยที่บันทึกไว้เพื่อวินิจฉัยโรคโดยการประมวลผลสัญญาณมักจะใช้รูปแบบของการแปลงของสัญญาณในโดเมนเริ่มต้นไปเป็นสัญญาณในโดเมนอื่นเพื่อให้พิจารณาเห็นรูปแบบลักษณะเด่นของสัญญาณที่เด่นชัดขึ้นกว่าเดิม เป้าหมายสำคัญของการวิจัยครั้งนี้คือการจำแนกรูปแบบสัญญาณของคนปกติ, ผู้ป่วยที่มีอาการหัวใจเต้นช้ากว่าปกติ, ผู้ป่วยที่มีอาการหัวใจเต้นเร็วกว่าปกติและอาการภาวะหัวใจห้องบนเต้นผิดปกติที่สัมพันธ์กับการเพิ่มขึ้นของอัตราการเสียชีวิตและปัจจัยเสี่ยงต่อโรคหลอดเลือดสมอง โดยใช้การแปลงเวฟเล็ตแบบเต็มหน่วยและตัวจำแนกโครงข่ายประสาทเทียมแบบฟัซซี่ซึ่งเป็นวิธีที่ผสมผสานวิธีโครงข่ายประสาทเทียมและ ฟัซซี่ลอจิก ค่าค่าสัมประสิทธิ์การแปลงเวฟเล็ตแบบเต็มหน่วยถูกใช้ในการหาความสัมพันธ์ของสัญญาณคลื่นไฟฟ้าหัวใจขาเข้าซึ่งก็คือ ค่าพลังงาน, ค่าสูงสุด, ค่าต่ำสุด, มัชฌิมเลขคณิต และค่าส่วนเบี่ยงเบนมาตรฐานของสัญญาณ ต่อมาการสกัดคุณลักษณะเด่นจะถูกวิเคราะห์และจำแนกโดยใช้ระบบอนุมาณโครงข่ายประสาทเทียมแบบฟัซซี่แบบปรับตัวซึ่งก็คือตัวจำแนกโครงข่ายประสาทเทียมแบบฟัซซี่ อัลกอริทึมที่นำเสนอมีการใช้งานและผ่านการทดสอบซอฟต์แวร์การวิเคราะห์เชิงตัวเลข สัญญาณคลื่นไฟฟ้าหัวใจที่ถูกเลือกและผ่านการทดสอบจาก

ฐานข้อมูล ฟิสิโอเน็ต โดยใช้ฐานข้อมูลย่อย สถาบันเทคโนโลยีแมสซาชูเซตส์-ศูนย์การแพทย์เบ็ธ อิสราเอลดีคอนเนส โดยระบบอนุมาณโครงข่ายประสาทเทียมแบบฟัซซี่แบบปรับตัวประสบผลสำเร็จในการจำแนกสัญญาณของคนปกติ, ผู้ป่วยที่มีอาการหัวใจเต้นช้ากว่าปกติ, ผู้ป่วยที่มีอาการหัวใจเต้นเร็วกว่าปกติและอาการภาวะหัวใจห้องบนเต้นผิดปกติ ที่ความถูกต้องเท่ากับ 98.41% มีค่าความไวในการทดสอบแต่ล่ะคลาสเท่ากับ 98.27%, 95.68%, 100% และ 98.48% ตามลำดับ และค่าความจำเพาะในการทดสอบแต่ล่ะคลาสเท่ากับ100%, 97.87%, 98.14% และ 98.36% ตามลำดับ

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Year	2015	

The objective of this study is to emphasize the advancement in methods for atrial fibrillation (AFib) analysis related to the risk factor of stroke utilizing fuzzy neural network and signal processing. The experiment procedures are initial from evaluation of overall EKG waveform shape and pattern enables clinicians to explore likely illnesses. Presently, signal processing to make a diagnosis a patient on the basis of EKG recording using the computer based analysis. Signal processing usually takes the form of a conversion of a domain into another domain that is in some logic, more desirable than the original. The purpose of this study is to address in identifying the Normal, Bradycardia Arrhythmia, Tachycardia Arrhythmia and Atrial Fibrillation (AFib) signal are related to an augmented death and risk of stroke utilizing the Discrete Wavelet Transform (DWT) method and Neuro-Fuzzy classifier, an Artificial Neural Networks hybrid method and Fuzzy Logic. DWT coefficients are used to extract the significant data from the EKG input records which are Energy, Standard Deviation value Maximum, Minimum, and Mean. Therefore the extracted features data is analyzed and classified utilizing Adaptive Fuzzy Inference Neural Network (AFINN) as a Neuro Fuzzy classifier. The proposed algorithm is implemented and also tested in numerical analysis software. The EKG signals are being selected and tested from PhysioNet Database utilizing MIT-BIH Arrhythmia Database. The AFINN system effectively

categorizes the Normal, Bradycardia Arrhythmia, Tachycardia Arrhythmia and AFib signal with the rate of accuracy is 98.41%. The analysis system also can achieved the sensitivity up to 98.27%, 95.68%, 100% and 98.48%, respectively for each class tested and the specificity value of Normal, Bradycardia Arrhythmia, Tachycardia Arrhythmia and AFib class proposed by AFINN are 100%, 97.87%, 98.14% and 98.36%, respectively.

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Researchers

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Chapter 1
Introduction

Background

Approximately 15-21% of stroke patients have atrial fibrillation (AFib) (Jørgensen, Nakayama, Reith, Raaschou, & Olsen, 1996) that the most common cardiac arrhythmia is related to an increased risk of systemic embolization including ischemic stroke. Nowadays, 2 and 2.5 million people in Europe and the U.S. respectively, have AF, and not only its incidence is as high as 10% in old-aged patients (>80 years old), but the mortality risk also increases to 1.5-1.9 compared to healthy populations in the same age group (Alcaraz & Rieta, 2010), whereas in Thailand, the prevalence of AFib is 5 per 100,000 populations (Kiatchoosakun, Pachirat, Chirawatkul, Choprapawan, & Tatsanavivat, 1999). 15% of patients with AFib who developed stroke, including transient ischemic attack (TIA) and no disabling or minor ischemic stroke, develop stroke recurrence in the first year, thereafter this risk increases 5% annually. Thus, anticoagulation therapy for secondary stroke prevention is very considerable for clinical management in these patients (Koudstaal & Koudstaal, 1999).

The presence of the electrical activity of the heart contraction is defined as an electrocardiogram (EKG) can be recorded automatically and quickly. This one is dissimilar noninvasive, meaning that the ECG signal can be measured without the need to insert the entire body (Raez, Hussain, & Mohd-Yasin, 2006). Electrodes are placed through the skin of the user to determine the potential bioelectric given off by the heart to the skin's surface to quantity the heartbeat regular position at the attendance of any damage illustrated heart and cardiovascular disease or illness data. The equipment is used to control cardiac pacemakers. (Harland, Clark, & Prance, 2003). Electric natural causes heart muscles to contract and pump blood through the heart to the rest of the body and lungs. The potential electricity produced by the operation of electrical appliances in heart tissue to signal biological EKG to convert the electrical activity of heart into tracings lines on paper, shown in Figure 1.1 and sharp decline in tracings line will be named wave. P wave, QRS complex and the T wave ST segment.

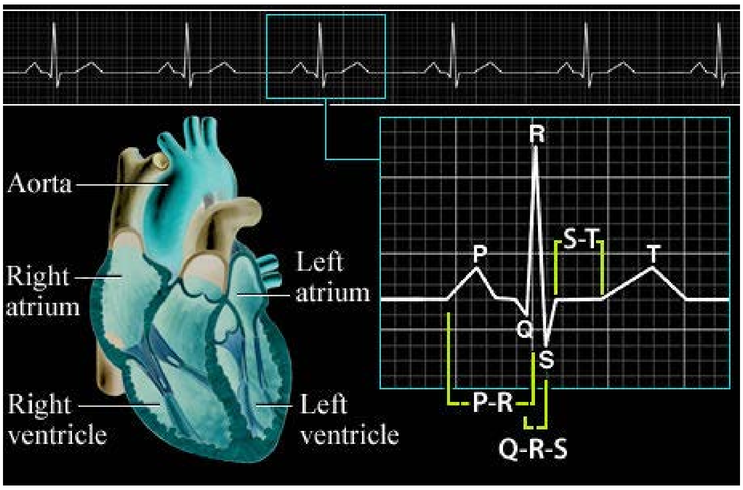


Figure 1.1 Diagram of the human heart and an example of normal EKG trace (Custodio, Herrera, López, & Moreno, 2012)

The heart is a muscular pump made up of four chambers as shown in Figure 1.1. The two upper chambers are named atria, and the two lower chambers are named ventricles. A natural electrical system causes the heart muscle to contract and pump blood through the heart to the body rest and the lungs (Chen, Chang, & Lee, 2015). The P wave is a record of the electrical activity through the upper heart chambers (atria). The QRS complex is a record of the movement of electrical impulses through the lower heart chambers (ventricles). The ST segment corresponds to the time when the ventricle is contracting but no electricity is flowing through it. The ST segment usually appears as a straight, level line between the T wave and the QRS complex. Then, the T wave corresponds to the period when the lower heart chambers are preparing for their next muscle contraction and relaxing electrically. In the medical test utilizing EKG, the cardiovascular disease detection is based on the difference wave signals that appear on the screen during the EKG test. The detection of the pulse is usually detected on the basis of the largest in a signal of PQRST of EKG signal. The normal heart beat in a regular rhythm will reveal the line tracing of T wave and the PQRS looks normal. If there any obvious the PQRST line tracing changes, it reveals that the heart may having a problems. Comparison of overall EKG waveform shape and pattern enables doctors to identify diseases. The EKG remains the simplest noninvasive distinguishing method for various cardiovascular diseases. In order to accurately characterize heart rate analysis, so a precise and reliable EKG waveform recognition scheme is necessary. The data and measurement waveform of the EKG signal is to extract features (characteristic) from the signal. The features are sufficiently representative of the physical process and the cardiovascular disease problem. Previous studies prove that frequency analysis sufficiently represents EKG waveforms; therefore frequency analysis is utilized to extract features from the EKG signal. The shapes of the EKG waveforms of dissimilar persons are different, so the differences of the waveform can be used to identify the dissimilar individual's characteristic. The EKG signal can varies from person to person because of the differences in position, size anatomy of the heart, age, sex relative body weight and also chest configuration.

In the past, many works of utilizing procedures for EKG analysis have been investigated and the successful results are achieved. So anyway, mostly the works are regarding to the specific disease checking system with so many limitations. Nowadays, many researches of the EKG waveforms detection methods for instance, Genetic Procedures, Artificial Neural Networks, Wavelet Transform, Pattern Comparison and other methods has been done in order to get the accurate, fast and better categorization signal.

As noticed, the EKG analysis system is quite complicated because of the system needs a proper algorithm to make sure the level of accuracy is very high. From the past studies, most systems of EKG analysis system are characterized based on the cardiovascular disease that will be quantify by the system and each types of cardiovascular disease is evaluated based on the characteristic of the heart signal. It is quite huge of signal types since the EKG signal itself can represent hundreds of cardiovascular disease. The system really needs a high efficiency 021.0 and safe because the health care is the most considerable in our life.

A trained people can easily recognizes the heart failure by manually searching thousands of heartbeats. But the several considerable heart cycle movements are also very small and rapid and cannot be able to catch by the human vision. It cause the level of classifying in order to detect the cardiovascular disease is not accurate. So it needs an excellent algorithm that every single event of heart signal cycle can be catch correctly and each characteristic of each cardiovascular disease signal must be studied to make sure the signals represent the correct disease. This characteristic needs critical evaluation to detect the suitable cardiovascular disease. Therefore, the procedures proposed must be high precision of detection and exact classifiers are needed to obtain a successful operation and can give earlier notification to the patients. But it is very hard to select the procedures that can suite with all of the disease. At least an algorithm with high accuracy levels and reduced level of false are really needed to be approved. In order to minimize such limitations of the EKG analysis system, a system of EKG system analysis incorporates with Fuzzy Neural Network and Discrete Wavelet transforms has been developed that can detect the disease properly.

The EKG analysis system is one of the bio signal processing areas that involve the computer science and engineering application to visualize and detect the biological processes. It is knowledge and significant tools to the diseases study to apply advanced technology to the complex problems of medical care that essential to enhance the appropriate treatment and patient living quality. This study is considerable because it can be used by the other health care professionals including physicians, nurses, therapists and technicians to bring together knowledge from many technical sources to develop new procedures, or to solve clinical problems.

The EKG analysis system can bring the possibility to record the heart condition at early stage that the problem is being hard interpretation for non-trained people. Therefore the importance in developing the system that makes this interpretation easier for non-trained people and the system could detect the disease with high levels of accuracy because many people who died cause of cardiovascular disease showed no outward symptoms. The results of EKG analysis utilizing the proposed algorithm are able to be used in the patient monitoring system that can be used in a hospital, transport, or emergency response environment.

Research Objectives

1.To evaluate the performance of EKG analysis utilizing DWT and AFINN that can allow for more accurate diagnoses in classifying the cardiovascular disease.

2.To determine the viability of EKG signal and characterization of EKG waveform in classifying the cardiovascular disease problem.

3.To implement an analysis system for EKG signals utilizing Discrete Wavelet Transform (DWT) and Adaptive Fuzzy Inference Neural Network (AFINN) as a Fuzzy Neural Network classifier.

Scope of Research

This study focuses on a group of middle-aged and elderly (age> 35 years) in rural and remote areas outside the municipality in the northern lower comprising nine provinces of Phitsanulok, Tak, Phetchabun, Sukhothai, Uttaradit, Nakhon Sawan, Uthai Thani, Kamphaeng Phet and Phichit implementation period of one year. A system of EKG analysis which operates by Discrete Wavelet Transform and Adaptive Fuzzy Inference Neural Network is developed. During operation, the analysis from the variation input signal based on the P, Q, R, S and T wave of EKG waveform are evaluated. The systems are able to recognize the dissimilar types of input wave from dissimilar people. The varying input signals based on few peoples are being tested on the same instruction. Then EKG module will determine the dissimilar data data from dissimilar people. In this study, the system has been conducted utilizing numerical analysis software.

The numerical analysis simulation will be used to determine the output from the various EKG signals. Four parameters are considered in the present study based on the P, Q, R, S and T wave signals which are Normal, Bradycardia Arrhythmia, Tachycardia Arrhythmia and AFib signals. These parameters are completely patient independent which means the learning data is independent of the testing data. The data used is from the Physionet Database. The signal parameters being stimulated by utilizing the procedures of DWT and the DWT coefficient from the values of Energy, Maximum, Minimum, Mean and Standard Deviation is fed into the AFINN classifier and then the coefficients will be used.

Limitation

The increased of input nodes used in AFINN model will cause increasing of the number of rules, so that it will affect to increase the time to run the sample data used in the training process of the AFINN system. The increasing of input nodes also will cause the networks to learn more complex functions and relatively increase the number of training epochs to complete the learning process until the root mean square error close into zero error rates. There are many types of cardiovascular disease which their EKG signals vary closely in amplitude and time duration and represent the expected disease. So the signals must be understood and recognize clearly to make sure the signals are not misclassified.

Research Hypothesis

1. People in the Northern Region are at high risk for cardiovascular disease and stroke.
2. The theory of Analysis of atrial fibrillation related to autonomic nervous system function in stroke patients utilizing fuzzy neural network and prediction parameter to assess the health risk of cardiovascular disease effectively.

Definitions of study Terms

AFib:	Atrial Fibrillation-Irregular heart rhythm
Agnosia:	Inability to recognize an object by touch alone
Agraphia:	Difficulty in writing or drawing
Alexia:	Inability to read
Amnesia:	Loss of memory
Aneurysm:	Swelling in a blood vessel wall which may burst and cause a stroke
Angioplasty:	Procedure to stretch narrowed coronary arteries to improve the blood flow to the heart
Aphagia:	Inability to swallow
Aphasia:	Inability to speak or use language
Apraxia:	Difficulty in coordinating movement or speech
Ataxia:	Loss of control of muscle function
ASA:	Aspirin-Blood thinning medication
ASD:	Atrial Septal Defect-Small hole in the top part of the heart

Atheroma:	Build up of fatty deposits in the blood vessels which restricts blood flow
Atherosclerosis:	Build up of fatty deposits in the blood vessels which restricts blood flow
AVM:	Arteriovenous Malformation-Abnormal structure of arteries and veins in the brain which has a risk of haemorrhage.
BP:	Blood Pressure-Measurement of the pressure within the arteries
Brain attack:	New term for a stroke
Brainstem:	Base of the brain which controls basic life functions
Bruit:	Noise made by a blockage in a Carotid Artery when examined by a doctor
Carotid Arteries:	Blood vessels which supply blood to the brain
CD:	Carotid Doppler-Ultrasound of the arteries in the neck to check for blockages
Carotid-Endarterectomy:	Procedure to clear blockage from a Carotid Artery
Cerebral-Haemorrhage:	Medical term for a bleed in the brain
Cardiac-Arrhythmia:	A group of conditions in which the muscle contraction of the heart is irregular or is faster or slower than normal.
Cholesterol:	Fat which leads to fatty deposits in the arteries
CT scan:	Computerized Tomography Scan-Two dimensional scan used to look at areas of the body in detail
CVA:	Cerebrovascular Accident Outdated medical term for a stroke
Contracture:	When a joint becomes fixed in one position
Defuzzification-Output:	Fuzzy sets is taking as input, Defuzzification outputs a crisp value which suitable for analysis.

Diplopia:	Double vision
DWT coefficient:	Parameter extracted from the wavelet analysis utilizing the filtering process
Dysarthria:	Difficulty in communicating because of weakness of the muscles used in speaking
Dysphagia:	Difficulty in swallowing
Dyslexia:	Difficulty in reading
Dysphagia:	Difficulty in swallowing
Dysphasia:	Difficulty in utilizing and understanding language
Dysphonia:	Difficulty in speaking at the desired volume
Dyspraxia:	Difficulty in coordinating movement or speech
EEG:	Electroencephalogram-Tracing of the activity of the brain
Electrocardiogram:	An electrical recording of the heart and is used in the investigation of cardiovascular disease.
Embolism:	A clot in a blood vessel that has been carried by the blood from one point in the circulation to lodge in another point.
Fuzzy rule:	A consequent of a rule of fuzzy set that represent by a membership function. The consequent is reshaped utilizing a function related to the antecedent.
Hemianopia:	Blindness in half of the visual field in both eyes
Hemiparesis:	Weakness or partial Paralysis on one side of the body
Hemiplegia:	Loss of power or movement on one side of the body
Haemorrhage:	Bleeding from a ruptured blood vessel
Haematoma:	Blood clot
HBP:	High Blood Pressure-When the pressure within the arteries is too high
Hydrocephalus:	Raised pressure within the skull
Hypertension:	High Blood Pressure
Hypotension:	Low blood pressure
Incontinence:	Loss of bladder or bowel control

Infarct:	Area of tissue damaged by lack of blood and oxygen
Input fuzzification:	The step to take the input s and determine the degree to which they belong to each of the appropriate fuzzy sets via membership functions.
Ischaemia:	A restriction in blood supply, generally because of factors in the blood vessels, with resultant damage or dysfunction of tissue. 'Isch' means reduced and 'emia' means blood. Myocardial ischemia is caused because of lack of sufficient blood supply to the cells, and may lead to myocardial infarction and in extreme cases, even death.
LACS:	Lacunar Syndrome-Medical categorization a stroke in one of the brain's smaller arteries.
Mean:	Provides a score that each case would have if the variable were distributed equally among all observations. The arithmetic average.
Median:	A score that separates all of the observations (frequencies) into two equal-sized groups.
MID:	Multi infarct Dementia-Long term confusion caused by a series of small strokes
NG:	Nasogastric Tube inserted through the nostril into the stomach to feed a Dysphagic patient
Nystagmus:	Involuntary jerking of the eyes
PACS:	Partial Anterior Circulation Syndrome-Medical classification; a Stroke at the front of the brain caused by an Infarct.
Paralysis:	Loss of movement in a part of the body
PEG:	Percutaneous Endoscopic Gastrostomy-Tube inserted into the wall of the stomach to feed a Dysphagic patient
PET:	Positive Emission Tomography-A detailed scan of the brain

POCS: Posterior Circulation Syndrome-Medical classification; a stroke at the back of the brain caused by an Infarct.

SAH: Subarachnoid Haemorrhage-Ruptured blood vessel bleeding into the space surrounding brain

Standard Deviation: A quantity of dispersion, based on deviations from the mean, calculated by taking the square root of the average squared deviations of each score from the mean.

Spasticity: Stiffness which develops in the muscles

Statin: Generic name for cholesterol lowering medications

Stroke: Disruption in the blood supply to part of the brain which damages the surrounding brain cells

TACS: Total Anterior Circulatory Syndrome-Medical classification; a large stroke at the front of the brain caused by an Infarct

Thalamus: Part of the brain which deals with sensations

Thrombolysis: A ‘clot busting’ drug used to dissolve a blood clot which is cautilizing a stroke

Thrombosis: Blockage in a blood vessel because of a blood clot

TIA: Transient Ischaemic Attack-Medical categorization of a mini-stroke; symptoms last less than 24 hours

Vertigo: An abnormal sensation of movement

VSD: Ventricular Septal Defect-Small hole in the bottom part of the heart

Warfarin: A prescribed blood thinning medication to prevent stroke because of embolism

Projected Benefits of the Research

1. A new method for analysis of atrial fibrillation related to autonomic nervous system function in stroke patients.

2. Techniques to develop fuzzy neural network to analyze the disorders of the heart.

3. Findings can be published in a national or international journals have at least one issue and can be applied to hospitals or health centers in rural areas more effectively.

Chapter 2
Theory and Related Research

History of Atrial Fibrillation and Its Treatment

A cardiac arrhythmia characterized by rapid, irregular, unorganized electrical and mechanical activity of the atria is defined as atrial fibrillation (AFib). That one is the most common sustained arrhythmia in human, with incidence and prevalence in general population of about 1 - 2% and 0.2%, respectively, and it is related to an increased mortality and risk of stroke (Benjamin et al., 1998; Feinberg, Blackshear, Laupacis, Kronmal, & Hart, 1995; Fuster et al., 2006). The quantity of AFib increases strongly with age: while the prevalence in a population 50 years old is about 1%, it increases to about 10% in octogenarians (Benjamin et al., 1998; Feinberg, Blackshear, Laupacis, Kronmal, & Hart, 1995; Fuster et al., 2006). More than 85% of AFib patients have symptoms for instance, palpitations, shortness of breath and fatigue, AFib patients having also significantly lower quality of life (Reynolds, Lavelle, Essebag, Cohen, & Zimetbaum, 2006). Control of ventricular rate during AF, anticoagulation therapy to reduce the risk of stroke and maintenance and restoration of sinus rhythm (SR) are the three treatment lines considered in every AFib patient, and also employed in most of them (Fuster et al., 2006).

Because of the maintenance, symptoms and restoration of SR has in most cases been an aim in the treatment of AFib. So anyway, it has been shown during the last decade that the rhythm control strategy aiming for SR does not improve the survival of AFib patients compared to the rate control strategy where SR is not aimed at. The rhythm control strategy can even be related to higher mortality, especially if antiarrhythmic medications are used (Caldeira, David, & Sampaio, 2012; Perez, Touchette, DiDomenico, Stamos, & Walton, 2011; Van Gelder et al., 2002). Paradoxically, the presence of SR has, so anyway, been related to better survival, better exercise capacity and quality of life (Chung et al., 2005; Deedwania et al., 1998; Epstein, 2004; Opolski et al., 2004; Thrall, Lane, Carroll, & Lip, 2006). Therefore it seems that the treatment modalities at least pharmacological ones that are so far available on the market to maintain and restore SR are not safe enough. It has been asserted that transvenous AFib ablation could be a safe and effective management for symptomatic AFib, and it has also been related to better survival of AFib patients when compared in an unblinded, non-randomised setting to a patient group treated with antiarrhythmic agents (Pappone et al., 2003; Sherzer et al., 2007). In a recently published trial a new antiarrhythmic drug, also decreased the number of cardiovascular deaths dronedarone, and increased the likelihood of SR (Hohnloser et al., 2009). Those results might encourage attempts at maintenance and restoration of SR with safer and newer methods.

The long-term results of the maintenance and restoration of SR are generally poor, perhaps reflecting the natural trend of AFib to turn out to be more stable in an individual with AFib (Kopecky et al., 1987). In prospective studies SR is maintained for a one-year period after electrical cardio version (CV) in only about 20% of patients if antiarrhythmic agents are not used, while the percentage is about 40 - 50% with common antiarrhythmic, and about 70% with amiodarone (Fuster et al., 2006; Lafuente-Lafuente, Mouly, Longas-Tejero, & Bergmann, 2007). The proportion of patients free from AFib after one year of transvenous AFib ablation has been about 70% in experienced centers when a substantial proportion of patients have had more than one scheme (Cappato et al., 2005; Lubitz, Fischer, & Fuster, 2008). It is also very apparent that regardless of the treatment given for example CV, transvenous AFib ablation or surgical AFib ablation some critical features seem to have a great influence on the number of patients who continue in AFib or have an AFib relapse. The most often repeated factors decreasing the likelihood of SR have been the age of the patient, the duration of AFib and the size of the (left) atrium (Berruezo et al., 2007; Beukema et al., 2008; Dittrich et al., 1989; Van Gelder et al., 1996; Vasamreddy et al., 2004; Viko, Marvin, & White, 1923). All these factors reflect or are surrogates of degeneration of atrial tissue; increased fibrosis during aging, atrium getting accustomed to AFib during the arrhythmia (“AFib begets AFib”) and atrial distension because of AFib itself or because of other cardiovascular diseases (Allessie, Ausma, & Schotten, 2002; Morillo, Klein, Jones, & Guiraudon, 1995; Nattel, 2002; Wijffels, Kirchhof, Dorland, & Allessie, 1995). This phenomenon is named atrial remodeling that is at least to some extent fundamental for AFib to be initiated and especially to be maintained.

AFib tends to increase in frequency and duration. Therefore, and particularly because our traditional pharmacological approaches have only a limited safety-to-efficacy profile, so-called “up-stream therapies” are warranted and investigated in order to prevent primary events of AFib and to decrease the frequency and duration of AFib episodes. We do not have any treatment against aging, but suppression of the renin-angiotensin-aldosterone system (RAAS) seems to decrease the development of atrial fibrosis and also to prevent AFib at least in patients with hypertension and heart failure (Boldt et al., 2006; Burstein & Nattel, 2008; Healey et al., 2005; Li et al., 2001). When a patient gets symptomatic AFib it is crucial that the treatments are started as soon as likely and SR is restored without any additional delay to prevent irreversible atrial remodeling from taking place (Van Gelder & Hemels, 2006).

The present series of studies is focused on atrial remodeling and atrial fibrillation, a common and fascinating arrhythmia that can be investigated from numerous perspectives. This work was started with a clinical evaluation of patients with persistent AFib referred for elective CV. Thereafter the center of attention was to study the atrial remodeling and reverse remodeling after CV with MCG. Two post-hoc analyses studying AFib of two prospective randomized trials evaluating RAAS suppressing medication are included to this work, because they have extended understanding of nature and importance of AFib.

The first documented observations of pulse have been found in ancient Chinese and Egyptian manuscripts. It was noticed very early that fast and irregular pulse was related to poor prognosis (Lip & Beevers, 1995; Lüderitz, 2002). Perhaps the first description of AFib is in The Yellow Emperor’s Classic of Internal Medicine (“Huang Ti Nei Ching Su Wen”). He was also a physician and is believed to have ruled China between 2697 and 2598 BC. (Lip & Beevers, 1995).

William Harvey (1578-1657) performed experimental work with animals, and the most valued of his work was the description of blood circulation. So anyway, he is also probably the first to describe AFib - “fibrillation of the auricles” – in animals, at least in recorded history (Flegel, 1995; McMichael, 1982). The first instrument to observe heartbeat was the stethoscope, invented by René Laennec (1781-1826), and soon after Laennec’s invention the association of irregular pulse and mitral stenosis was documented by Robert Adams (1791-1875) (Lip & Beevers, 1995). Documentation of

AFib became likely with ECG. The first human EKG was recorded by Augustus Waller (1856-1922) in 1887, and in 1906 Willem Einthoven (1860-1927) described the first EKG of AFib as “pulsus inaequalis and irregularis” (Fye, 2006; Lüderitz, 2002). Soon thereafter it was noticed that AFib was “a common clinical condition” in patients with cardiovascular diseases (Lewis, 1909).

Explanation of the nature and concept of AFib was advanced in the late 1800s and the early 1900s. Even though fibrillation or undulation of the atria was established in animal experiments, the similarity with the irregular pulse of a patient was not documented until 1907 (Flegel, 1995). In the first EKG recordings of AFib atrial activity during AFib was considered an artefact, but in 1909 it was noticed that there was irregular atrial electrical activity in AFib. In addition Thomas Lewis (1881-1945) noticed that atrial and ventricular rhythms were disordered and that the venous pulse was of ventricular type, lacking normal atrial contraction (Lewis, 1909).

In documented Western medical history, treatment of AFib was first described by William Withering (1741-1799), who gave digitalis AFib to patients with heart failure. He discovered that irregular pulse became more regular and symptoms were relieved when digitalis was administered (Lip & Beevers, 1995). With EKG a precise diagnosis of AFib was likely and the treatment of patients became more accurate. As early as 1749 it was noticed that cinchona bark had a beneficial effect on irregular pulse, and in the late 1910s cardio version of AFib was performed with quinidine and documented with EKG (Lüderitz, 2002). During the 20th century an overwhelming expansion of medical knowledge has given us all the other antiarrhythmic drugs to restore and maintain SR and beta blocking agents to control the ventricular rate of AF.

In the 1950s experimental work with defibrillators revealed that cardiac arrhythmias could be stopped with alternating current (AC) counter shock (Gall & Murgatroyd, 2007; Gibson, Linenthal, Norman, Paul, & Zoll, 1956; Lown, Amarasingham, & Neuman, 1986; Zoll, Linenthal, Gibson, Paul, & Norman, 1956). This method was, so anyway, very robust, and the response was unpredictable. Bernard Lown made extensive experiments with defibrillation, and he observed that AC counter shocks were associated in EKG with changes of acute myocardial infarction and caused mortality. In addition, he noticed that there was a vulnerable period in late systole, and a counter shock given during this period caused ventricular arrhythmia. These inconveniences were solved with the implementation of QRS-complex synchronized direct current (DC) cardiac counter shock and defibrillator (Lown et al., 1986). The scheme documented by Lown differs very little from that performed today, and the greatest progress since the 1960s has been the invention of the biphasic cardiac defibrillator (Gall & Murgatroyd, 2007).

Atrial Fibrillation Epidemiology

The categorization and nomenclature of AFib has previously varied, cautilizing large discrepancy between the studies published. At present, AFib has been classified with good clinical relevance and simplicity, and the nomenclature has obtained international consensus (Fuster et al., 2006; Lévy et al., 2003). The currently accepted definition of AFib as 1) paroxysmal AFib – episodes that last less than or equal to 7 days and are self-terminating, 2) persistent AFib – episodes lasting usually more than 7 days and 3) permanent AFib – long-lasting episodes where cardio version has failed or is no longer attempted – was launched in 2001 in the ACC/AHA/ESC guidelines that were updated in 2006 (Fuster et al., 2006). Most of the earlier studies did not make any distinction between the types of AF, or the type of AFib was not documented. Therefore, if the type of AFib is not established and published, the prevalence mentioned has to be considered as including all AFib. So-called “lone atrial fibrillation” is defined as a status where an AFib patient does not have any concomitant cardiovascular disease or diagnosis predisposing to AFib (Fuster et al., 2006).

Prevalence of AFib in General Population

The first publication about the prevalence of AFib in general population was written by Ostrander et al. They performed epidemiological investigation in the town of Tecumseh, Michigan, USA, where almost 90% of the total population had a complete medical examination with 12-lead EKG (Ostrander Jr, Brandt, Kjelsberg, & Epstein, 1965). More than 5,000 adult citizens were evaluated, 22 of whom (0.4%) had AFib. They also found that AFib was more prevalent among older citizens, and four of the six who had AFib and were less than 60 years old had rheumatic cardiovascular disease.

The ATRIA study was a large-scale evaluation performed within Kaiser Permanente in Northern California. This health care organization takes care of nearly 3 million members. The prevalence of AFib in population ≥ 20 years old was 0.95%, comprising almost 18,000 AFib patients. Among patients older than 55 years, AFib appeared to be more common in white (2.2%) than in black (1.5%) patients (Go et al., 2001). Even if the population served by the organization was vast, there were some limitations in this study. First, the health care organization in question did not cover all the care given in the area, having some skewness for example in household income compared to Northern California population as a whole. In addition, they excluded patients with transient AFib and hyperthyroidism. Based on the determined prevalence in the studied population Go et al. estimated that during the cohort assembly period in the late 1990s there were nearly 2.3 million US adults with non-transient AFib. In addition, they estimated that this number would increase 2.5-fold to more than 5.6 million by the year 2050 because of the increase in the number of elderly persons (Go et al. 2001).

One study in England and Wales and another in Scotland have estimated the prevalence of AFib in general practice settings in Great Britain (Majeed, Moser, & Carroll, 2001; Murphy et al., 2007). These studies also had a very remarkable size of registered populations served by the National Health Service; 1.4 million and 360,000, respectively. The prevalence of AFib in England and Wales was 12.1/1,000 in men and 12.7/1,000 in women, the corresponding records in Scotland being 9.4/1,000 and 7.9/1,000 (Majeed, Moser, & Carroll, 2001; Murphy et al., 2007).

The main limitation in studies with patients of health care registers is that patients with asymptomatic AFib are not included. The question of asymptomatic AFib was recently enlightened by Fitzmaurice et al. who documented that screening in order to find all the AFib patients could increase the prevalence of AFib in general practice environment about 1.6-fold (Fitzmaurice et al., 2007). The Framingham Heart Study (FHS) is a large-scale follow-up study based on cohorts in Framingham, Massachusetts, USA. The study started in the late 1940s with more than 5,000 adult subjects, and AFib has been one of the main topics evaluated over the decades, giving us numerous publications describing the epidemiology of AFib (complete biography: www.framinghamheartstudy.org). The main findings of FHS regarding the prevalence of AFib have been that AFib is seen in 0.5% at age 50-59 years and in up to almost 9% in octogenarians, the prevalence of AFib is increasing, and men have an about 1.5-fold greater age-adjusted risk of AFib than women (Kannel et al., 1998). Figure 2.1 reveals the prevalence of AFib in several epidemiologic studies in general population.

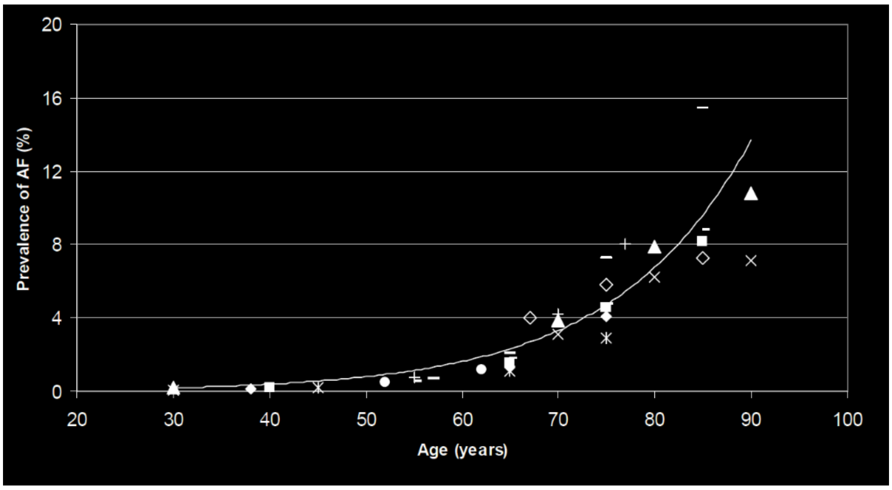


Figure 2.1 The prevalence of AFib in ten epidemiologic studies in general population

Atrial Fibrillation Incidence

Many of the studies mentioned in the previous chapter have also had databases to explore the incidence of AFib. So anyway, since the incidence of a disease is a time-dependent subject, cross-sectional study design is not valid, and a follow-up of the population studied is needed. Another method to evaluate the incidence of AFib is to screen for a "new AFib" that is defined as AFib not diagnosed earlier in a particular patient.

Cardiovascular Health Study (CHS) studied a population ≥ 65 years old and also had a follow-up aspect. During their average follow-up of 3.3 years the incidence of AFib was 19.2 per 1,000 person-years (Psaty et al., 1997). The Mayo Clinic in Rochester, Minnesota serves almost completely the surrounding Olmsted County, and the incidence of AFib in that population has risen from 3.0 per 1,000 person-years to 3.7 per 1,000 person-years from 1980 to 2000 (Miyasaka et al., 2006). Based on these results Miyasaka et al. estimated the number of AFib patients in the US to be 12 million by 2050 that is more than 2-fold assumed by the ATRIA study investigators, even if the age-adjusted incidence of AFib remains stable (Go et al., 2001; Miyasaka et al., 2006).

The European perspective on AFib incidence in general health care setting is based on British health care databases. In a Scottish study the incidence of AFib was 0.9 per 1,000 person-years in patients older than 45 years (Murphy et al., 2007). Ruigómez et al. had a very large General Practice population of approximately 3 million residents (Ruigómez, Johansson, Wallander, & Rodríguez, 2002). They reported the incidence rate of chronic AFib to be 1.7 per 1,000 person-years in residents aged 40-89 years (Ruigómez, Johansson, Wallander, & Rodríguez, 2002). So anyway, those studies were cross-sectional, without any follow-up, and therefore they most probably underestimate the real incidence of AFib in those populations. For that reason they are not included in Figure 2.2

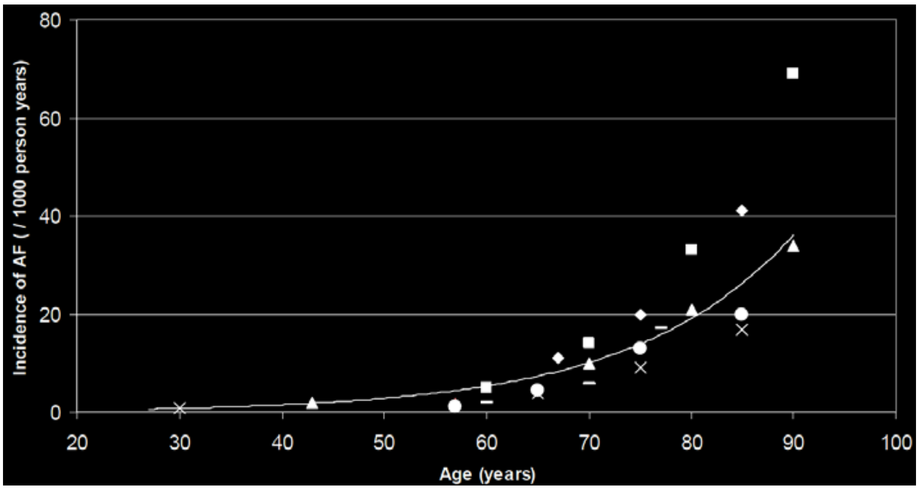


Figure 2.2 The incidence of AFib in seven epidemiologic studies in general population

Epidemiology of Paroxysmal, Persistent and Permanent AF

Based on the Framingham database the prevalence and incidence of chronic and transient AFib has been assumed to be of the same order (Kannel, Abbott, Savage, & McNamara, 1983). There also seems to be a common pattern of short episodes of AFib to lengthen and a tendency of recurrent or paroxysmal AFib to become persistent and chronic AFib (Humphries et al., 2001; Kerr et al., 2005; Kopecky et al., 1987; Lévy et al., 1999). The number or percentage of AFib patients arriving for elective electrical cardio version in a population-based study setting has not been documented before. In addition, the rate of progression from paroxysmal to persistent AFib has been estimated to be 8.0% at 1 year (Lévy et al., 1999), but there are no published data regarding the progression rate from persistent AFib treated with cardio version to permanent AF.

Conditions Predisposing to AFib in General Population

Ostrander et al. already documented higher prevalence of AFib in citizens with increasing age and rheumatic cardiovascular disease (Ostrander et al., 1965). Practically all of the studies considering the prevalence and incidence of AFib have also evaluated the predisposing factors or associated conditions to AFib. The spectrum and quantity of predisposing conditions have very large variability in relation to the study period and the population studied. The most striking change in AFib patients' profile has been the proportion of patients with rheumatic valvular disease that has nearly disappeared in developed countries (Fuster et al., 2006; Lévy et al., 1999; Ostrander Jr et al., 1965).

At population level, age is the strongest independent risk factor for AFib (Fuster et al., 2006; Greenlee & Vidaillet, 2005). Quite constantly about 75% of AFib patients are reported to be ≥ 65 years old and the mean age of AFib patients is approximately 70 years (Fuster et al., 2006; Go et al., 2001; Majeed et al., 2001; Miyasaka et al., 2006; Ruigómez et al., 2002). The odds ratio of the increased risk of AFib for age has been estimated to be 1.05-1.11 per year or 2.1-2.2 per decade (Benjamin et al., 1994; Frost, Hune, & Vestergaard, 2005; Psaty et al., 1997; Stewart, Hart, Hole, & McMurray, 2001; Wilhelmsen, Rosengren, & Lappas, 2001). Increasing atrial fibrosis during aging is maybe the most considerable reason for the association between aging and AFib (Allessie et al., 2002).

Male sex predisposes to AFib with an age-adjusted odds ratio of about 1.4-1.8 (Allessie et al., 2002; Kannel et al., 1998; Miyasaka et al., 2006; Ruigómez et al., 2002; Stewart et al., 2001). So anyway, because of the longer life expectancy in the female population, the number of male and female AFib patients is about the same. The reason for the higher propensity to AFib in males might be the greater stature and therefore larger atria of men and also their higher alcohol consumption (Greenlee & Vidaillet, 2005).

Great stature and especially obesity (BMI ≥ 30) is very strongly related to increased risk of AFib (Dublin et al., 2006; Frost et al., 2005; Ruigómez et al., 2002; Wang et al., 2004). This is of great importance, bearing in mind the increasing proportion of obese people in Western countries. Miyasaka et al. estimated in their paper that a 60% increase in age- and sex-adjusted risk of AFib could be attributed to obesity. If this trend continues the number of AFib patients in the United States could be as high as 15.9 million by 2050, accounting for about 3% of the population (Miyasaka et al., 2006). Even if a favorable effect of weight loss on P-wave duration and P-wave dispersion has been shown there are no data documenting suppression of AFib with weight loss (Duru, Seyfeli, Kuvandik, Kaya, & Yalcin, 2006).

Hypertension is the background diagnosis that is most often related to AFib. With modern, strict criteria the prevalence of hypertension is 44% in European adults and 28% in North American adults (Wolf-Maier et al., 2003). The proportion of AFib patients having diagnosed hypertension varies from 25% to 80% and the odds ratio for AFib with a diagnosis of hypertension is 1.5 - 1.8 (Benjamin et al., 1998; Frost et al., 2005; Go et al., 2001; Lévy et al., 1999; Miyasaka et al., 2006; Murphy et al., 2007; Ruigómez et al., 2002). Atrial remodeling caused by hypertension was determined as a prolongation of P-wave in signal-averaged EKG (SAECG) by Madu et al. and by Aytemir et al. showing that P-wave prolongation – a well-known indicator of the risk of AFib – is strongly related to hypertension. The P-wave duration was also related to the severity of hypertension (Aytemir, Aksoyek, Yildirir, Ozer, & Oto, 1999; Madu, Baugh, Gbadebo, Dhala, & Cardoso, 2001). Since those studies did not include echocardiographic data, it is not known whether the longer P-wave duration in hypertensive patients is a result of the established association between hypertension and left atrial enlargement (Vaziri, Larson, Lauer, Benjamin, & Levy, 1995). Indeed, it has been shown that treatment of hypertension – at least with ACE (angiotensin-converting enzyme) inhibitors – is associated with shortening of P-wave (Zaman, Kearney, Schecter, Worthley, & Nolan, 2004). LVH measured by either echocardiography or EKG is a well-known risk factor of AFib (Kannel et al., 1998; Stewart et al., 2001). LVH is both an indicator of stressed left ventricle, most often because of hypertension, and of LV diastolic dysfunction affecting atrial emptying and pressure. In the FHS, LVH in EKG was related to a 3.0 - 3.8-fold increased risk of AFib (Kannel et al., 1998).

Heart failure is both a cause and a consequence of AF, and it is diagnosed in 20-35% of AFib patients (Dagres et al., 2007; Kannel et al., 1998; Miyasaka et al., 2006; Ruigómez et al., 2002). There is, so anyway, some disagreement with echocardiographic findings, where AFib patients seem to have well-preserved left ventricular (LV) systolic function. For example, in the FHS patients with and without AFib had fractional shortenings of 37.1% and 38.6%, respectively (Kannel et al., 1998). In clinical practice it is likely that AFib patients – because of older age – have more often diastolic dysfunction that with high ventricular rate during AFib might predispose to symptomatic heart failure without diminished LV systolic function. In the FHS, diagnosed heart failure was related to a 4.5- and 5.9-fold risk of AFib in men and women, respectively (Kannel et al., 1998). Patients with severe heart failure have the highest reported incidence of AFib. In a patient group referred for evaluation of heart transplantation new AFib was diagnosed in 8.1% of patients during a mean 19 months of follow-up (Pozzoli et al., 1998).

There is no reliable estimation of the proportion of valvular cardiovascular disease in AFib patients. In the FHS 24.7% of AFib patients had mitral annular calcification compared to 11.9% of patients without AF, but in the CHS valvular disease was diagnosed in only 3.8 – 8.0% of AFib patients (Kannel et al., 1998; Psaty et al., 1997). At present, valvular cardiovascular disease is seldom found as a causative factor for AFib in clinical practice in the developed countries (Fuster et al., 2006; Wilhelmsen et al., 2001).

Impact of AFib in General Population

Heart failure has a dual association with AF, being both a cause and a consequence of AFib. As mentioned earlier, heart failure is diagnosed in about 20% of AFib patients, and in the presence of heart failure, development of AFib is highly increased. In the Framingham material the dual roles of AFib and heart failure were very convincingly documented, as it was found that in AFib subjects the subsequent development of CHF was related to increased mortality with a hazard ratio of 2.7 in men and 3.1 in women. Correspondingly, in patients with heart failure, development of AFib was related to a hazard ratio of mortality of 1.6 in men and 2.7 in women (Wang et al., 2003). A good rate control has been the key means to avoid heart failure, since the published data have previously not proven any benefit on mortality from interventions to restore and maintain SR in either patients with normal or with depressed LV systolic function (Roy et al., 2008; Tuinenburg et al., 1999; Van Gelder et al., 2002; Wyse et al., 2002). In the recently published ATHENA trial AFib patients were treated with a new antiarrhythmic drug, dronedarone, and those randomized to the active drug benefited, with an increased likelihood of SR as well as a decreased number of cardiovascular deaths (Hohnloser et al., 2009). Those results might encourage intentions aimed at maintenance and restoration of SR with newer and safer methods.

The increased risk of stroke in AFib patients was first documented in the FHS, being 5.6 times as frequent compared to the cohort without AF, while the risk of stroke in patients with rheumatic cardiovascular disease was 17.6-fold (Wolf, Dawber, Thomas, & Kannel, 1978). In the Mayo Clinic material 1.3% of patients with lone AFib had a stroke during a 15-year follow-up that is similar to expected rates (Kopecky et al., 1987). A recent analysis of the same database revealed that this risk of stroke in lone AFib patients continues to be the same as expected up to 25 years, but becomes significantly higher when the follow-up is extended to more than 30 years (Jahangir et al., 2007). On average, the rate of stroke among patients with non-valvular AFib and without anticoagulation therapy is 5% per year that is 2 to 7 times that of a comparable population without AFib. The risk of stroke tends to be equal in patients with sustained and paroxysmal AFib (Fuster et al., 2006; Hohnloser et al., 2007).

Most studies assessing mortality in an AFib population comparable to a population without AFib have found an increased risk of all-cause death in AFib patients. Mortality is approximately 1.5- to 2-fold with AF, and this excess mortality is seen among cardiovascular causes of death. The impact of AFib on the risk of death seems to be stronger in new AFib compared to an old diagnosis of the arrhythmia (Benjamin et al., 1998; Fuster et al., 2006; Kannel et al., 1998; Lévy et al., 1999; Vidaillet et al., 2002).

The Electrocardiogram Diagnosis Techniques for Cardiovascular Disease

In the earlier 1980, according to the Centers for Disease Control and Prevention, United States, cardiovascular disease is the leading cause of death for both women and men almost in the world and it is also a major cause of disability. In the worldwide, coronary cardiovascular disease kills more than 7 million people each year. Cardiovascular disease is a broad term that includes several more specific heart conditions which are Coronary Heart Disease, Heart Attack, Ischemia, Arrhythmias, Cardiomyopathy, Congenital Heart Disease, Peripheral Arterial Disease (PAD).The most common heart condition is coronary heart disease that can lead to heart attack and other serious conditions and the study from PubMed Central Journals reveals that the Ischemia is the most common cause of death in the industrialized countries. So the earliest diagnosis and treatment utilizing electrocardiography (EKG) has been developed to observe the disease signal. Papaloukas et al. has indicated that the development of suitable automated analysis techniques can make this method very effective in supporting the physician's diagnosis and in guiding clinical management. In recent year, numerous study and algorithm have been developed for the work of analyzing and classifying the EKG signal. The classifying method which have been proposed during the last decade and under evaluation includes digital signal analysis, Fuzzy Logic methods, Artificial Neural Network, Hidden Markov Model, Genetic Algorithm, Support Vector Machines, Self-Organizing Map, Bayesian and other method with each approach exhibiting its own advantages and disadvantages. Researchers including Li et al. and Hu et al. have studied that the EKG features can be extracted in time domain and Minami et al., Moraes et al. and Papaloukas et al. have studied in frequency domain. Some of the features extraction methods implemented in previous study includes Discrete Wavelet Transform, Karhunen-Loeve Transform, Hermitian Basis and other methods. (Ahmadian, Karimifard, Sadoughi, & Abdoli, 2007; Cuesta-Frau, Pérez-Cortés, Andreu-García, & Novák, 2002; Hu, Palreddy, & Tompkins, 1997; Jager, 2002; C. Li, Zheng, & Tai, 1995; Lin & Chang, 1989; Minami, Nakajima, & Toyoshima, 1999; Moraes, Seixas, Vilani, & Costa, 2002; Papaloukas et al., 2003).

Discrete Wavelet Transform

Features extraction is extracting and converting the input data data into a set of features which named feature vector, by reducing the data representation pattern. The features set will extract the relevant data from the input data in order to perform the categorization task. The transform of a signal is just another form of representing the signal. It does not change the data content present in the signal. Wavelet theory is the mathematics related to building a model for a signal, system, or process. A wavelet is a wave which has its energy concentrated in time. It has an oscillating wavelike characteristic but also has the ability to allow simultaneous time and frequency analysis and it is a suitable tool for transient, non-stationary or time-varying phenomena. WT has a varying window size, being broad at low frequencies and narrow Wavelet theory is the mathematics related to building a model for a signal, system, or process. A wavelet is a wave which has its energy concentrated in time. It has an oscillating wavelike characteristic but also has the ability to allow simultaneous time and frequency analysis and it is a suitable tool for transient, non-stationary or time-varying phenomena. WT has a varying window size, being broad at low frequencies and narrow at high frequencies, thus leading to an optimal time-frequency resolution in all frequency ranges.

Figure 2.3 Diagrams of sinusoidal signal and Daubechies wavelet

From the Figure 2.3 above, the signals with sharp changes might be better analyzed with an irregular wavelet than with a smooth sinusoid, as quoted in Mahmoodabadi et al. (2005). Also, local features can be described better with wavelets that have local extent. The Wavelet Transform uses multi-resolution method by which dissimilar frequencies are analyzed with dissimilar resolutions. It is capable of representing signals in dissimilar resolutions by dilating and compressing its basis functions. The basis function in wavelet analysis is defined by two parameters which are scale and translation. A basis function which is mother wavelet is used in wavelet analysis. For a wavelet of order N, the basis function can be represented in Equation below.

$$\psi(n) = \sum_{j=0}^{N-1} (-1)^j c_j (2n + j - N + 1)$$

The Discrete Wavelet Transform (DWT) that is a time-scale representation of the digital signal is obtained utilizing digital filtering techniques, is found to yield a fast computation of Wavelet Transform. It is easy to implement and adopts dyadic scales and translations in order to reduce the quantity of computation time that results in better efficiency of calculation. The DWT which also referred to as decomposition by wavelet filter banks is calculated by successive low pass filter (LPF) and high pass filtering (HPF) of the discrete time domain signal as the process shown graphically in Figure 2.4.

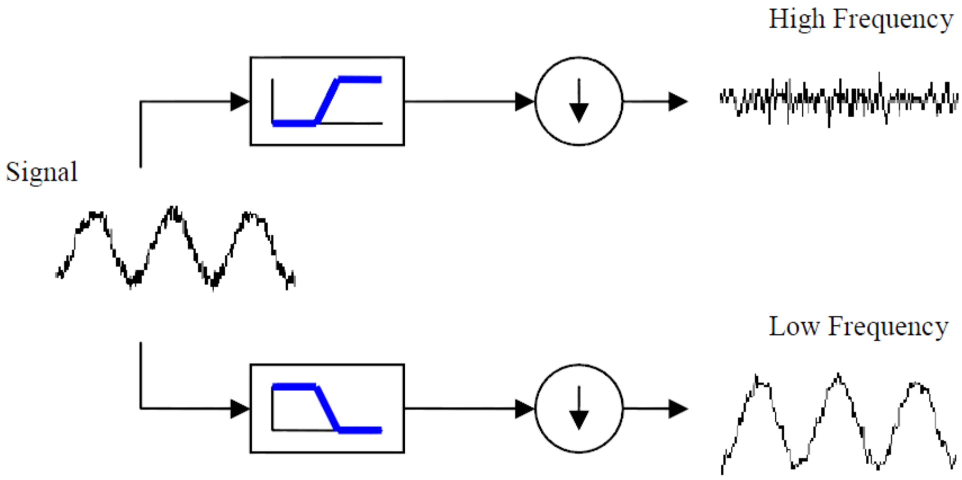


Figure 2.4 Filter banks signal decomposition

The dissimilar cutoff frequencies are used for the analysis of the signal at dissimilar scales to quantity the quantity of detail data in the signal and the scale is determined by up sampling and down sampling process where D and A denoting for details and approximations, while c representing coefficients. The approximations of the signal are what define its identity while the details only imparts nuance.

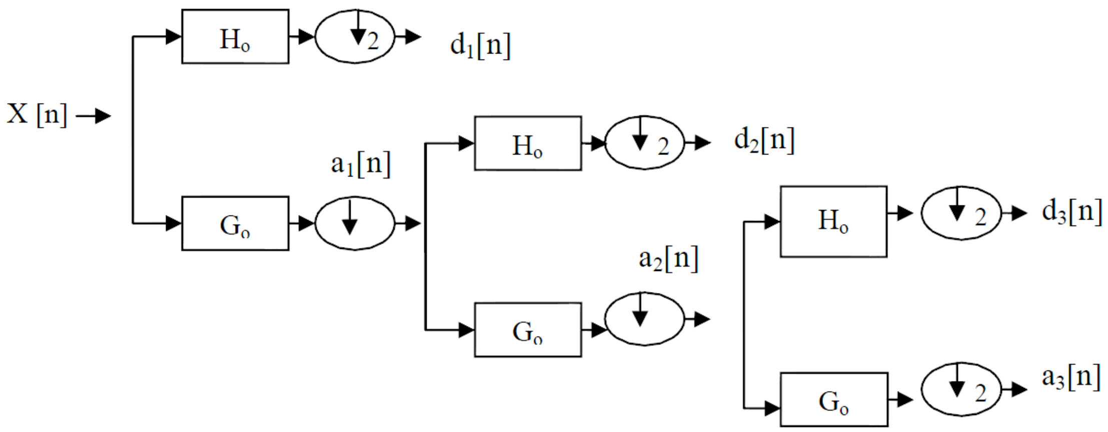


Figure 2.5 Wavelet decomposition trees

Figure 2.5 reveal the decomposition process is iterative that connects the continuous-time multi-resolution to discrete-time filters. The signal is denoted by the sequence input signals *x*[n], where n is an integer passed through a series of high-pass filters to analyze the high frequencies, and through a series of low-pass filters to analyze the low frequencies. Each stage consists of two digital filters and two down samplers by 2 to produce the digitized signal. The low pass filter is denoted by G_o while the high pass filter is denoted by H_o. At each level, the high pass filter produces detail information; d[n], while the low pass filter related to scaling function produces coarse approximations, a[n]. The down sampled outputs of first high pass filters and low-pass filters provide the detail, *D*1 and the approximation, *A*. The first approximation, *A*1 is decomposed again and this process is continued. The filtering and decimation process is continued until the desired level is reached. The maximum number of levels depends on the length of the signal. Only the last level of approximation is save among all levels of details that provides sufficient data. The DWT of the original signal is then obtained by concatenating all the coefficients, a[n] and d[n], starting from the last level of decomposition. The signal decomposition can mathematically be expressed in Equation below:

$$y_{hi}[k] = \sum x[n] \cdot \mathrm{g}[2\,\mathrm{k} - \mathrm{n}]$$

$$y_{lo}[k] = \sum x[n] \cdot h[2\,\mathrm{k} - \mathrm{n}]$$

With this approach, the time resolution becomes arbitrarily good at high frequencies, while the frequency resolution becomes arbitrarily good at low frequencies. In DWT the signals can be represented by approximations and details. The detail at level j is defined as:

$$D_j = \sum_{k \subset z} a_{j \cdot k} \psi_{j \cdot k}(t)$$

Where, Z is the set of positive integers. Then, the approximation at level J is defined as:

$$A_i = \sum_{j > J} D_i$$

Finally, the signal f (t) can be represented by:

$$f(t) = A_j = \sum_{j \le J} D_j$$

In DWT where a scaling function is used that are related to low-pass and high-pass filters, respectively. The scaling function can be represented as Equation below:

$$\Phi(n) = \sum_{j=0}^{N-1} c_j \Phi(2n - j)$$

$$\Phi_{j \cdot k}(\mathrm{t}) = 2^{j/2} \Phi(2^j t - k)$$

Fuzzy Neural Network categorization Algorithm

Decision making of categorization was performed in two stages: selection of coefficients computing by DWT and the AFINN classifiers. Four types of EKG beats (Normal, Tachycardia Arrhythmia, Bradycardia Arrhythmia, and AF) obtained from the PhysioBank databases will be classified by AFINN classifiers.

Fuzzy Neural Network Approach

Fuzzy Neural Network is a hybrid of artificial neural networks and fuzzy logic, which Fuzzy Neural Network networks are the realizations of the functionality of fuzzy systems utilizing neural techniques. Fuzzy Neural Network incorporates the human-like reasoning style of fuzzy systems through the use of fuzzy sets and a linguistic model consisting of a set of IFTHEN fuzzy rules as shown in Figure 2.6.

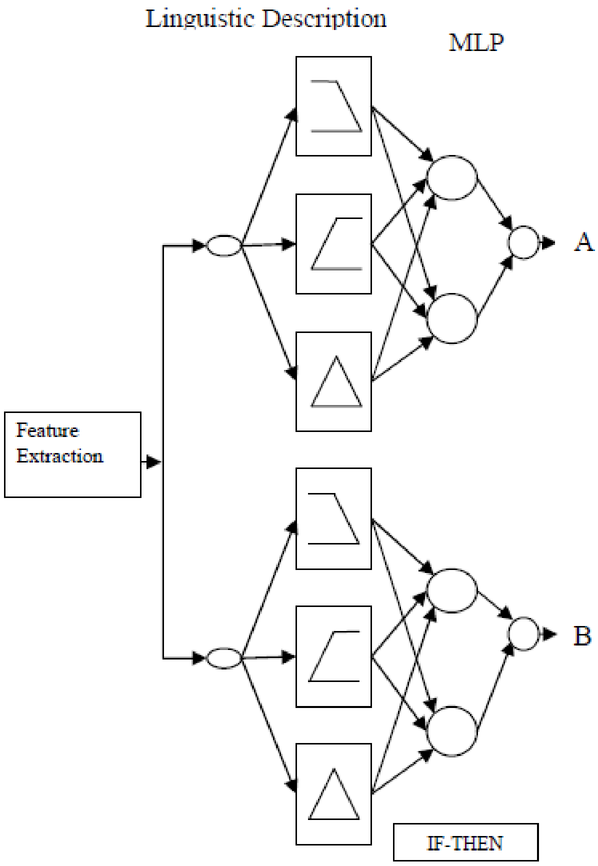


Figure 2.6 Structure of feed-forward fuzzy neural network

The considerable part of fuzzy layer, it is responsible to analyze the distribution of data and group the data into the dissimilar membership values. This membership value is applied as the input vector to the Multi-Layer Perceptron Neural Network classifier. The membership value also representing the parameter of each heart beat class. This study use the output of DWT method as features vector and AFINN as a Fuzzy Neural Network classifier for the EKG analysis, because based on the previous research; the accuracy rates achieved by the combined neural network model presented for categorization of the EKG beats were to be higher than standalone classifier model. The Fuzzy Neural Network is also more tolerant to the noise and less sensitive to the morphological changes of the EKG characteristic and AFINN also plays a considerable role in dealing with uncertainty when making decisions in medical application.

Adaptive Fuzzy Inference Neural Network

AFINN stands for Adaptive Fuzzy Inference Neural Network. This method brings the learning capabilities of neural networks to fuzzy inference systems. In AFINN, Takagi-Sugeno type Fuzzy Inference System (FIS) is used. The learning algorithm tunes the membership functions Takagi-Sugeno type utilizing the training input-output data. The output of each rule can be a linear combination of input variables. The final output is the weighted average of each rule’s output. The embedded fuzzy system in a neural fuzzy network can self-adjust the parameters of the fuzzy rules utilizing neural network learning procedures to achieve the desired results.

The parameters related to the membership functions are open to change through the learning process. The computation of these parameters (or their adjustment) is facilitated by a gradient vector that provides a quantity of how well the AFINN is modeling the input output data for a given parameter set. Once the gradient vector is obtained, back propagation or hybrid learning algorithm can be applied in order to adjust the parameters. Basic AFINN architecture that has two inputs x and y and one output z is shown in Figure 2.7.

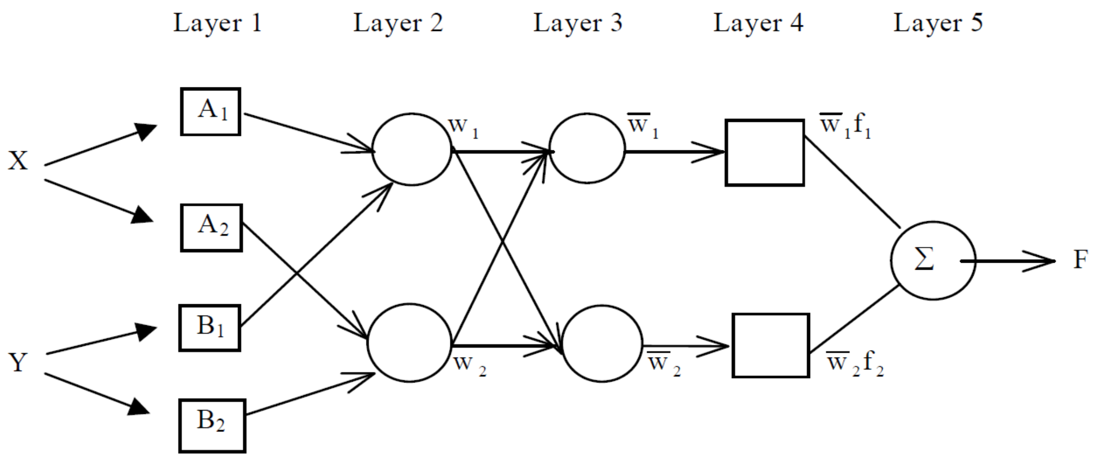


Figure 2.7 Basic structure of AFINN model

Two Takagi-Sugeno if-then rules are shown in Equation below.

$$Rule1: If\ x\ is\ A_1\ and\ B_1\ then\ f_1 = p_1 x + q_1 y + r_1$$

$$Rule2: If\ x\ is\ A_2\ and\ B_2\ then\ f_2 = p_2 x + q_2 y + r_2$$

The nodes functions of AFINN architecture in the same layer are described below:

Layer 1: Every node *I* in this layer is a square node with a node function as in

$$0_{1,i} = \mu_{Ai}(x),\ for\ I = 1,2$$

$$0_{1,i} = \mu_{Bi-2}(x),\ for\ I = 3,4$$

where x is the input to node *I*, and *Ai* (or *Bi*−2) is a linguistic label (such as "small", "medium", "large") related to this node. The $0_{1,i}$ is the membership function of a fuzzy set *Ai* and it specifies the degree to which the given input x satisfies the quantifier *Ai* . Usually is chosen $U_{Ai}(x)$ to bell-shaped with maximum equal to 1 and minimum equal to 0, for instance, the generalized bell function in

$$\mu_{Ai}(x) = \frac{1}{1 + \left[\left(\frac{x - c_i}{a_i} \right)^2 \right]^{bi}}$$

or the Gaussian function represent in

$$\mu_{A_i}(x) = e^{-(\frac{x - c_i}{a_i})^2}$$

where a_i, b_i, c_i is the parameter set. The membership function for A_i can be any appropriate membership function, for instance, the Bell-shaped, Triangular or Gaussian. When the parameters of membership function changes, chosen membership function varies accordingly, thus exhibiting various forms of membership functions for a fuzzy set A_i. Parameters in this layer are referred to as "premise parameters".

Layer 2: Every node in this layer is a fixed node labeled as Π, whose output is the product of all incoming signals defined by

$$0_{2,i} = w_1 = \mu_{A_i}(x)\mu_{B_i}(\mathrm{y}),\ for\ I = 1,2$$

Each node output represents the firing strength of a fuzzy rule.

Layer 3: Every node in this layer is a fixed node labeled N. The *i*th node calculates the ratio of the rule's firing strength to the sum of all rules' firing strengths as represent by

$$0_{3,i} = \overline{w}_1 = \frac{w_i}{w_1 + w_2},\ for\ I = 1,2$$

Outputs of this layer are named "normalized firing strengths".

Layer 4: Every node *I* in this layer is an adaptive node with a node function in

$$0_{4,i} = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i)$$

where $\overline{w}_i$ is a normalized firing strength from layer 3 and $(p_i, y_i\ and\ r_i)$ is the parameter set of this node. Parameters in this layer are referred to as "consequent parameters".

Layer 5: The single node in this layer is a fixed node labeled Σ that computes the overall output as the summation of all incoming signals represent in

$$Overall\ output = 0_{5,i} \sum_i \overline{w}_i f_i = \frac{\sum iw_i f}{\sum iw_i}$$

Thus an adaptive network that is functionally equivalent to the Takagi-Sugeno type fuzzy inference system, has been constructed.

AFINN Implementation in Classifying Cardiovascular Disease

The categorization was performed utilizing the AFINN classifiers in Fuzzy Logic Toolbox. AFINN were trained with the back propagation gradient descent method in combination with the least squares method. The block of featured processed in AFINN were shown in Figure 2.8.

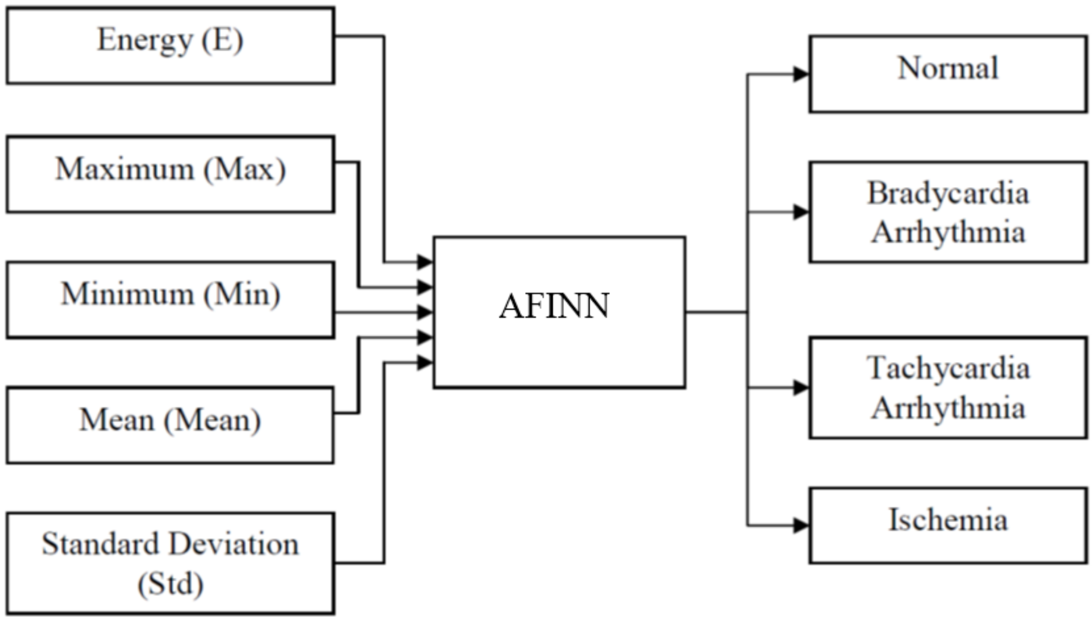


Figure 2.8 Block diagram of cardiovascular disease categorization through adaptive fuzzy inference neural network (AFINN)

Based on the Figure 2.8, the featured vector that is being computing from the DWT coefficient which are Energy, Maximum, Minimum, Mean and Standard Deviation were defined as extracted features for AFINN inputs and Normal, Bradycardia Arrhythmia, Tachycardia and AFib are defined as AFINN outputs.

Fuzzy Inference System

AFINN required a predefined network structure and its membership function as well as other parameters can be trained during the learning process. The system is first designed utilizing surgeon Fuzzy Inference System (FIS). There are two types of FIS namely Grid Partition and Subtractive Clustering. The AFINN Grid Partition was adopted in this study because this system required the number of membership functions for each input. This system uses the bell shaped membership function to characterize the fuzzy sets input and Surgeon output membership functions are linear types. In the Layer 1, there are five nodes have been used for each input dimension X_i where $i = 1,2,\ldots,d$ and d is the number of input dimensions. The AFINN which constructs a FIS, whose membership function parameters are tuned utilizing a back propagation algorithm in combination with a least squares type of method, will allows fuzzy systems to learn from the data that they are modeling. The FIS of cardiovascular disease categorization is shown in Figure 2.9.

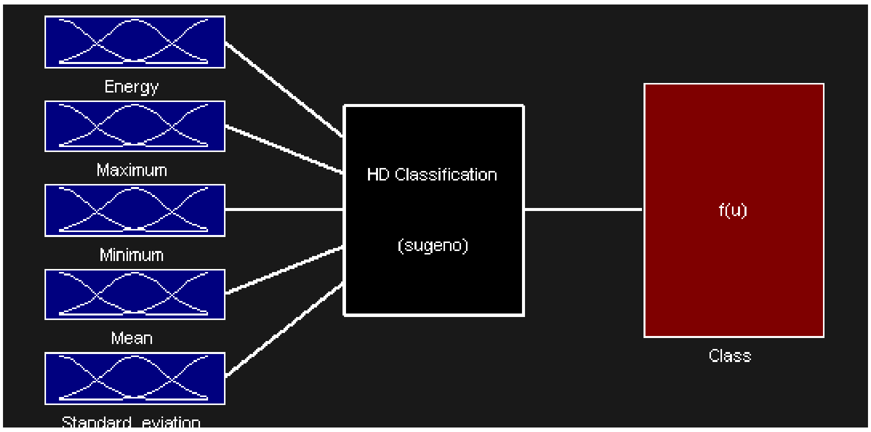
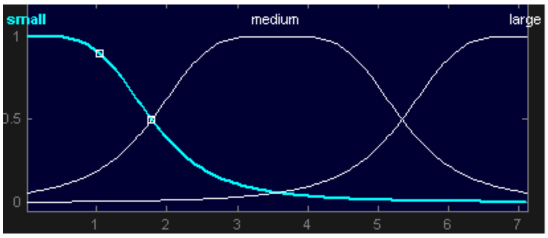
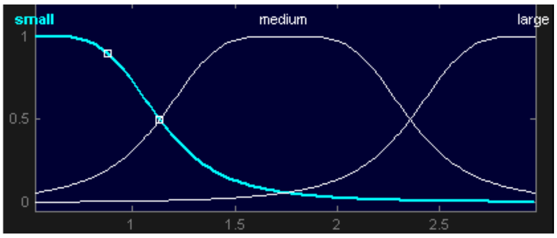


Figure 2.9 Fuzzy inference system for cardiovascular disease classification

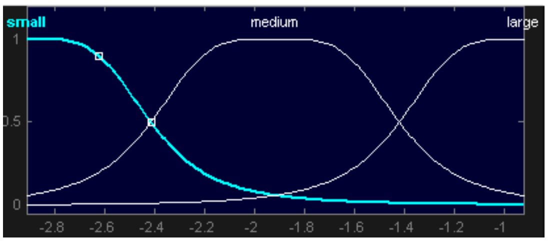
Based on five input-one output systems, the five variables were used which are Energy, Maximum, Minimum, Mean and Standard Deviation of DWT coefficients and the output class either Normal, Bradycardia Arrhythmia, Tachycardia Arrhythmia or AFib is taken as the output variable. The input parameters are represented by fuzzy set or linguistic variables. The membership functions for input variables are shown in Figure 2.10 (a-e).



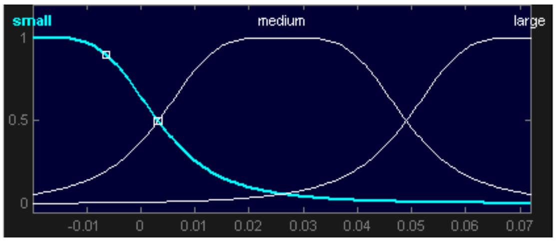
(a) Energy coefficients



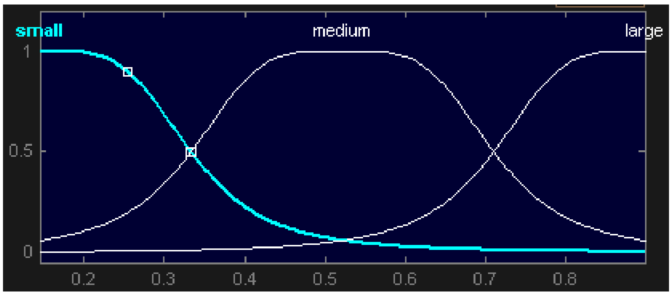
(b) Maximum coefficients



(c) Minimum coefficients



(d) Mean coefficients



(e) Standard deviation coefficients

Figure 2.10 Initial membership functions for each input dimensions

Based on Figure 2.10, the membership function of each input parameter was divided into three regions that are, small, medium and large. The examination of initial and final membership functions indicates that there are considerable changes in the final membership functions of the features.

Rule Base Identification

Based on the membership functions, then the fuzzy IF-THEN rules that have a fuzzy antecedent and constant consequence are constructed. The rule base was created according the expert knowledge utilizing numerical analysis rule base editor. Based on the three membership function (small, medium, large) that being used in this project, the number of rule base created by Equation:

$$a \wedge \mathrm{b} = \mathrm{c}$$

where; *a* is membership function

b is number of input nodes

c is number of rules output

Literature Review

The EKG analysis method required the classifier stage and feature extraction. In the previous EKG analysis research, the feature extraction methods include Discrete Wavelet Transform has been discussed by Thakor et al., Li et al. and Clarek, Optimal Mother Wavelet by Castro et al., Karhunen-Loeve Transform method by Jager, Hermitian Basis functions by Ahmadian et al. and other features extraction methods by nitric oxide Lin and Chang and Cuesta-Frau et al. and other features extraction methods (Ahmadian et al., 2007; Clark, Biscay, Echeverría, & Virués, 1995; Cuesta-Frau et al., 2002; Jager, 2002; Li, Zheng, & Tai, 1995; Lin & Chang, 1989; Thakor, Xin-rong, Yi-Chun, & Hanley, 1993).

Coast et al. described an approach to Cardiac Arrhythmia Analysis Utilizing Hidden Markov Models. This method classified by detecting and analyzing QRS complex and determining the R-R intervals to determine the ventricular arrhythmias. The Hidden Markov modeling approach combines structural and statistical knowledge of the EKG signal in a single parametric model. The Hidden Markov modeling addresses the problem of detecting low amplitude P waves in typical ambulatory EKG recordings. Zigel et al. presented the method of Synthesis Coding in their paper. The synthesis EKG compressor algorithm is based on analysis by synthesis coding, and consists of a beat codebook, long and short-term predictors, and an adaptive residual quantize. Predetermined distortion level is used in feature extraction of EKG signal. Their algorithm uses a defined distortion quantity in order to efficiently encode every heartbeat, with minimum bit rate, while maintaining a predetermined distortion level. Their proposed compression procedures were found to have the best performances at any bit rate as stated in their paper (Coast, Stern, Cano, & Briller, 1990; Zigel, Cohen, & Katz, 2000).

Li et al. use the Wavelet transforms method including Thakor et al., Cuesta-Frau et al., Pretorius and Nel and Mahmoodabadi et al. because the results indicated that the DWT-based feature extraction method yields superior performance. Li et al. has done the EKG analysis utilizing wavelet transform. This method can distinguish the between the QRS wave and P, T wave. This method also can distinguish noise, baseline drift and artifacts. So it can characterize the signal data analysis very well and suitable to process time-varying biomedical signals. The wavelet transforms also capable of representing signals in dissimilar resolutions by dilating and compressing its basis functions as explains by Clarek (Clark et al., 1995; Cuesta-Frau et al., 2002; C. Li et al., 1995; Mahmoodabadi, Ahmadian, Abolhasani, Eslami, & Bidgoli, 2005; Pretorius & Nel, 1992; Thakor, Xin-rong, Yi-Chun, & Hanley, 1993)).

Park et al. (2008) applied two morphological feature extraction methods which are higher-order statistics and Hermite basis functions. Their study results showed that hierarchical categorization method gives better performance than the conventional multiclass categorization method. They used the support vector machines to compare the feature extraction methods and categorization methods to evaluate the generalization performance. But the used of higher order models need more computation cost and caused over fitting problem in generalization performance. In term of accuracy, they found that their hierarchical categorization method showed better categorization performance than the conventional multiclass categorization method with despite the loss in accuracy and sensitivities certain classes. The hierarchical categorization improved the mean values of sensitivity mean. It agreed that their categorization method can distinguish the multiclass heartbeats with the unbalanced data distribution (Park et al., 2008).

Researcher Jager (2002) developed a new approach to feature extraction that is Karhunen Loeve transformed (KLT). Which is an attractive and powerful approach to the feature-extraction and shape representation process. It has the solution if the probability densities of population of pattern vectors of a problem domain are unknown. The problem with this method is it is too sensitive to a noisy pattern of EKG signal (Jager, 2002).

According to Ranjith et al. (2003) which used wavelet transforms to detect myocardial ischemia, the wavelet transform is obtained utilizing the quadratic spline wavelet. These correspond to the detection of T wave and P wave. Their methods shown this method is having a comparatively higher sensitivity and nominal positive predictivity value. It is also can be easily extended to detect other abnormalities of the EKG signal. But this method also has the limitation of this method is that the computations required are higher than those required by other methods. This is mainly because of the calculation of Wavelet Transform. According to Kadbi et al. (2006) in their paper highlighted those three features for features extraction stage which are time-frequency features, 2 - time domain features and 3 - statistical feature. These three features have been used in their project because these features can overcome the limitations of other methods in classifying multiple kinds of arrhythmia with high accuracy at once. These methods have been combined with PCA method to reduce the redundancy caused by the frequency coefficient in the feature dimension to make sure the average of the categorization accuracy can be increased. Tinati et al. (2006) in the studies used wavelet-transform based search algorithm to use the energy of the signal in dissimilar scales to isolate baseline wander from the EKG signal. They first remove the artifacts which is the noise that induced in EKG signals that result from movements of electrodes. The baseline wanders that are considered as an artifact can affect inaccurate data when measuring the EKG parameters. In their study utilizing the presented algorithm; it can eliminate the baseline drifts from the EKG signals without introducing any deformation to the signal and also from losing any clinical data of the signal (Kadbi, Hashemi, Mohseni, & Maghsoudi, 2006; Ranjith, Baby, & Joseph, 2003; Tinati & Mozaffary, 2006).

Christov et al. (2006) used the independent component analysis and matching pursuits for the features extraction for extracting additional spatial features from multichannel electrocardiographic recordings. It test the categorization performance of 5 largest classes of heartbeats in the MITBIH arrhythmia database which are Normal Sinus Beats (NSB), Left Bundle Branch Block (LBBB), Right Bundle Branch Block (RBBB), Premature Ventricular Contraction (PVC) and Paced Beats (PB). The performance of the system is remarkably good, with specificities and sensitivities for the dissimilar classes. They have a problem because the complicated separation between ventricular PBs and PVCs because of the inverted T wave (Christov et al., 2006).

Ahmadian et al. (2007) proposed a new piecewise modeling for approximation of EKG signal utilizing Hermitian Basis. This method uses only the 5th order Hermitian basis functions. This method yields to weighting the approximation error of each segment based on its importance throughout the EKG complex. This method reveals the total error obtained in this method is almost halved in comparison with similar nonsegmented method. The disadvantage of this method is a small error could mislead the diagnosis (Ahmadian et al., 2007).

The pattern recognition of the type of EKG waveform, there are dissimilar solutions presented in the literature have been proposed during the last decade and are under evaluation. In EKG training and categorization analysis stages, some researchers have tried to maximize the detection level of accuracy in many dissimilar ways for instance, digital signal analysis (Papaloukas et al., 2003), Fuzzy Logic methods (Bortolan et al., 1988; Lei, Li, Dong, & Vai, 2007; Zong & Jiang, 1998), Artificial Neural Network (Papaloukas et al., 2003; Pretorius & Nel, 1992; Silipo & Marches, 1998; Yang, Hu, & Shyu, 1997), Hidden Markov Model (Graja & Boucher, 2005; Hughes, Tarassenko, & Roberts, 2004), Genetic Algorithm (Goletsis, Papaloukas, Fotiadis, Likas, & Michalis, 2004), Support Vector Machines (Osowski, Hoai, & Markiewicz, 2004), Self- Organizing Map (Lagerholm & Peterson, 2000), Bayesian and other method with each approach exhibiting its own advantages and disadvantages. But the most recent systems employ artificial neural networks (Papaloukas et al., 2003) to perform diagnoses since they have demonstrated great consistency in producing accurate results. The performance of the developed detection systems is very promising but they need further evaluation. The automatic detection of EKG waves is considerable to cardiac disease diagnosis. A good performance of an automatic EKG analyzing system depends heavily upon the accurate and reliable detection of the disease.

Neural Network: The categorization of the EKG utilizing Neural Networks (NNs) has become a widely used method in recent years. The network architectures for modeling process modeling in NNs include the feed forward network, the radial basis function (RBF) network, recurrent network, and other advanced network architecture as explained by Silipo and Marches (Silipo & Marches, 1998). The efficiency of these classifiers depends upon a number of factors including network training. It has the inputs models in the training parameters and the output indicated the point at which training should stop.

In designing an EKG classifier based on Neural Network (NN), the normal scheme is to firstly train the network by presenting it with training data that is representative of the unknown data it is likely to experience during the categorization process. A well-chosen training algorithm, results in a NN which is capable of generating a non-linear mapping function with the capability of representing relationships between given EKG features and cardiovascular disease disorders. A well designed NN will exhibit good generalization when a correct input-output mapping is obtained even when the input is slightly dissimilar from the examples used to train the network. Nitric oxide Silipo and Marchesi (Silipo & Marches, 1998) also developed an Automatic EKG Analysis based on Artificial Neural Network. This project present the result by carrying out the categorization tasks for the most common features of EKG analysis which are arrhythmia, myocardial ischemia and chronic alterations and achieve high categorization accuracy. Another researches Papaloukas et al. (Papaloukas, Fotiadis, Likas, & Michalis, 2002)developed an automated method for the ischemic detection based on the recordings from European Society of Cardiology (ESC) ST-T database in order to train the network for beat categorization also achieve high accuracy rate.

According to nitric oxide Dayong et al. from the National University of Ireland which has developed a distinguishing system for cardiac arrhythmias from EKG data, utilizing an Artificial Neural Network (ANN) classifier based on a Bayesian framework. The Bayesian ANN Classifier is built by the use of a logistic regression model and the back propagation algorithm. A dual threshold method is applied to determine the diagnosis strategy and suppress false alarm signals. This system consists of three basic modules which are a Server, multiple Client Machines and BAN-Hubs which used real time patient bio signal data provides earlier data and high categorization accuracy (Dayong, Madden, Chambers, & Lyons, 2005).

Fuzzy Neural Network Approach: The idea of the EKG analysis and categorization utilizing Fuzzy Neural Network has been start around 1990, yet it remains one of the most considerable indicators of proper cardiovascular disease categorization today. The most difficult problem faced by an automatic EKG analysis is the large variation in the morphologies of EKG waveforms, it happens not only for dissimilar patients or patient groups but also within the same patient. So the Fuzzy Neural Network is the most suitable method because it is more tolerance to morphological variations of the EKG waveforms. Researcher Linh et al. have studied in depth on the Fuzzy Neural Network approach to the recognition and categorization of heart rhythms on the basis of EKG waveforms. It uses the new approach of heart beat recognition. This project is the resolution for the problem of less sensitivity to the morphological variation of the ECG. It combining two techniques which are characterization of the QRS complex of EKG by Hermite polynomials and utilizing the coefficients of Hermite kernel expansion as the features of the process and the application of the modified Fuzzy Neural Network TSK network for EKG pattern recognition and classification. The performance enhancement utilizing proposed method in Fuzzy Neural Network utilizing autoregressive model coefficients, higher-order cumulant and wavelet transform variances as features by Engin and Papaloukas et al. can solve the problem to detect more cardiovascular disease types in high accuracy. The Fuzzy Neural Network Techniques which refers to the combination of fuzzy set theory and neural networks with the advantages of both which are handle any kind of information, numeric, linguistic, logical, imperfect information, resolve conflicts by collaboration and aggregation, self-learning, self-organizing and self-tuning capabilities, no need of prior knowledge of relationships of data, mimic human decision making process, and fast computation utilizing fuzzy number operations in order to do the categorization task (Engin, 2004; Linh, Osowski, & Stodolski, 2003; Papaloukas, Fotiadis, Likas, & Michalis, 2003).

Hidden Markov Models: This method was successfully used since the mid-1970s to model speech waveforms for automatic speech recognition. The hidden Markov modeling approach combines structural and statistical knowledge of the EKG signal in a single parametric model. The model constructed contains multiple states per extraction field, model parameter and training procedures as explained by Coast et al, who described an approach to Cardiac Arrhythmia Analysis Utilizing Hidden Markov Models. This method classified by detecting and analyzing QRS complex and determining the R-R intervals to determine the ventricular arrhythmias. The Hidden Markov modeling approach combines structural and statistical knowledge of the EKG signal in a single parametric model. Model parameters are estimated from training data utilizing an iterative, maximum likelihood restoration algorithm. This method has ability of beat detection, segmentation and classification, with highly suitable to the EKG problem. Its approach addresses a waveforms modeling, multichannel beat segmentation and classification, and unsupervised adaptation to the patient’s EKG (Coast, Stern, Cano, & Briller, 1990). Cheng and Chan have discovered the method of

Hidden Markov Model in classifying arrhythmia. They have developed a fast and reliable method of QRS detection algorithm based on a one-pole filter which is simple to implement and insensitive to low noise levels. The disadvantages are that the observations are very sensitive to baseline wander, DC drift and heart rate variation. The HMM method also is not sufficient to represent one particular type of beat. This is because some beats exhibit large variations in the morphologies of their EKG signals. Therefore, several HMMs are needed for certain some beats (Cheng & Chan, 1998).

Support Vector Machine: The Support Vector Machine-Based Expert System that have been described by Burges (1998) and Osowski et al. (2004) also the best method to apply in EKG analysis. The recognition system that uses the support vector machine (SVM) working in the categorization mode. Support vector machines map input vectors to a higher dimensional space where a maximal separating hyperplane is constructed. Two parallel hyperplanes are constructed on each side of the hyperplane that separates the data. The separating hyperplane reveals the maximize distance. The larger the distance between these parallel hyperplanes, the better the generalization error of the classifier (Burges, 1998; Osowski, Hoai, & Markiewicz, 2004).

According to Osowski et al. (Osowski, Hoai, & Markiewicz, 2004) have performed their studies of Heartbeat Recognition utilizing Support Vector Machine-Based Expert System. This recognition system has used the dissimilar preprocessing methods for generation of features which are higher order statistics (HOS) while the second is the Hermite characterization of QRS complex for the registered EKG waveform. Their paper presented the combination of multiple classifiers by the weighted voting principle. In their studies, stated that a good recognition system should depend on the features representing the EKG signals in such a way, that the differences among the EKG waveforms are suppressed for the waveforms of the same type but are emphasized for the waveforms belonging to dissimilar types of beats. It is a considerable item, since the observed signal is a high variation of signals among the same types of beats. These two dissimilar preprocessing methods of the data, cooperating with SVM classifier, that have been integrated into one expert system have proven in improve the overall accuracy of heartbeat recognition. In previous project of the categorization of Myocardial Ischemia has been developed by Zimmerman and Povinelli (Zimmerman & Povinelli, 2004) to improve an algorithm for myocardial ischemia categorization created by Mohebbi and Moghadam (Mohebbi & Moghadam, 2007) of specificity value. The proposed procedures have been implemented with the support vector machine classifier. The radial basis function (RBF) has been used as the kernel of the support vector machine as a featured vector. But this proposed algorithm for myocardial ischemia categorization resulted that is not able to improve the method developed by Langley et al. It is happened because the tradeoff that occurs between specificity and sensitivity is too great. Increasing the specificity caused the sensitivity to drop, and automatically decreased the overall accuracy. So completely independent of the ST deviation values must be done in order to increase specificity and accuracy.

de Magalhaes et al. (de Magalhaes, Jahankhani, & Hessami, 2010)indicate the application of Support Vector Machine (SVM) in QRS detection utilizing entropy and combined entropy criterion. The advantages of utilizing SVM are the ability to find a hyperplane that divides samples in to two classes with the widest margin between them, and the extension of this concept to a higher dimensional setting utilizing kernel function to represent a similarity quantity on that setting. This algorithm performs better as compared with published results of other QRS detectors tested on the same database and depends strongly on the selection and the variety of the ECGs included in the training set, data representation and the mathematical basis of the classifier.

Self-Organizing Map: Meanwhile, in the EKG analysis of the Ischemia Detection with a Self-Organizing Map Supplemented by Supervised Learning has been developed in 2001 by Papadimitriou et al. (Papadimitriou, Mavroudi, Vladutu, & Bezerianos, 2001). It is to solve the problem of maximizing the performance of the detection of ischemia episodes. The basic self-organizing map (SOM) algorithm modified with a dynamic expansion process controlled with entropy based criterion that allows the adaptive formation of the proper SOM structure. This extension proceeds until the total number of training patterns that are mapped to neurons with high entropy reduces to a size manageable numerically with a capable supervised model. Then, a special supervised network is trained for the computationally reduced task of performing the categorization at the ambiguous regions only. The utilization of sNet-SOM with supervised learning based on the radial basis functions and support vector machines has resulted in an improved accuracy of ischemia detection.

Fuzzy logic: Zong and Jiang (Zong & Jiang, 1998) described the method of fuzzy logic approach single channel EKG beat and rhythm detection. The method summarized and makes use of the medical knowledge and distinguishing rules of cardiologists. Linguistic variables have being used to represent beat features and fuzzy conditional statements perform reasoning. The algorithm can identified rhythms as well as individual beats. This method also handling the beat features and reasoning process is heuristic and seems more reasonable as stated in their paper. It also presented that this method may be of great utility in clinical applications for instance, multi-parameter patient monitoring systems, where many physiological variables and distinguishing rules exist.

Bayesian: According to Dayong et al. (Dayong, Madden, Chambers, & Lyons, 2005) point out that the Bayesian network are improved methods in determining the arrhythmia diagnosis system. This method is able to deal with nonlinear discrimination between classes, incomplete or ambiguous input patterns, and suppression of false alarms. It develops new detection schemes with a high level of accuracy. This approach have been find out as a potentially useful for generating a pattern recognition model to classify future input sets for arrhythmia diagnosis. The Bayesian network have been proof that it have a capability of uncertainty management to work with the dual threshold method that could be used to control a diagnosis strategy and suppress false alarm signals in future improvement. Wiggins et al. (Wiggins, Saad, Litt, & Vachtsevanos, 2008) had evolving a Bayesian classifier for EKG classification. The patient's categorization was according to statistical features extracted from their EKG signals utilizing a genetically evolved Bayesian network classifier and the identification depends on the variables of interest. The Bayesian Network has an ability to handle missing data points and its lower requirement of data based on a priori knowledge of the system's variable dependencies is its major benefits. It is a relatively new tool that identifies probabilistic correlations in order to make predictions or assessments of class membership that could solved many complex problems exist in identifies the data for the variables of interest. This method shown it is very easy to implement, and one of the study area that are good to be discovered. The limitation of their studies has been the method for binary discretization used after feature extraction because of small size of the data set.

Genetic Procedures: EKG analysis nitric oxide including Nugent et al. (Nugent, Lopez, Smith, & Black, 2002) have studied in depth on the Prediction models in EKG classifiers utilizing genetic programming approach. In their studies they developed the prediction models to indicate the point at which training should stop for Neural Network based EKG classifiers in order to ensure maximum generalization. According to them, this good wave prediction could exhibit good generalization. They found that it could give benefit to developers of Neural Networks, not only in the presented case of Neural Network based EKG classifiers, but indeed any categorization problems.

Autoregressive Model: Ge et al. (Ge, Srinivasan, & Krishnan, 2002) have extended the study of Cardiac arrhythmia categorization utilizing autoregressive modeling. This Computer-assisted arrhythmia recognition have been proposed to classify normal sinus rhythm (NSR) and various cardiac arrhythmias including atrial premature contraction (APC), premature ventricular contraction (PVC), super ventricular tachycardia (SVT), ventricular tachycardia (VT) and ventricular fibrillation (VF). Their studies have shown the AR coefficients were classified utilizing a generalized linear model (GLM) based algorithm in various stages. From their study, they found that the AR modeling is useful for the categorization of cardiac arrhythmias, with reasonably high accuracies. From the study, they found that AR modeling based categorization algorithm has demonstrated good performance in classification. The procedures are also easy to implement and the AR coefficients can be easily computed. AR modeling can lead to a low cost, high performance, simple to use portable telemedicine system for EKG offering a combination of distinguishing capability with compression. Therefore, it revealed that enhancement is suitable for real-time implementations and can be used for compression as well as diagnosis.

Other methods: Bousseljot and Kreiseler (Bousseljot & Kreiseler, 1998) have introduced a new method for the EKG interpretation by waveform recognition without feature extraction process. Their studies found that the method for ECGs computer-aided interpretation by signal pattern comparison have presented many advantages which are it is no feature extraction for the EKG and also no limitation of the distinguishing statements. Their system also shown that it inclusion of rare diseases by specialized EKG databases and it have a possibility of extending the databases as bases of knowledge without changes of the algorithm. The method also performed robustness with respect to disturbances or signal failures in a lead and has learning ability by inclusion of the results of current patient examinations. Also, the study showed cost advantages by use of existing PCs and inclusion of further patient data from the database for making diagnoses.

Minfen et al. (Minfen, Chan, & Beadle, 2003) defines a new method for extracting time-varying rhythms utilizing multi-resolution decomposition to investigate the transition of clinical EEG signals. The method proposed in their paper is more flexible and accurate because of the better matching in time-frequency characteristics of EEG signal for extracting 4 kinds of EEG rhythms. The results of have demonstrated the superior performance of the new wavelet packet analysis algorithm. But this method still has problems which are the optimal segmentation length resolution for such analysis that is obviously related to the time varying characteristics of the EEG signals observed. So they need build an optimal segmentation-based adaptive algorithm to improve the result of the signal analysis.

A new Digital Filter Based Enhancement of QRS Complex of EKG for Improved Arrhythmia categorization has been discussed by Rodríguez et al. (Rodríguez, Mexicano, Bila, Cervantes, & Ponce, 2015). The filter is used in this method to enhance the QRS complex of the EKG wave. This algorithm is tried to prevent the problems that are normally encountered in detecting EKG characteristic points which are noise in the process of measurement, non-zero baseline, baseline drift, high P and T waves and artifacts. The algorithm gives remarkable improved the results of against noise, base-line drift and other problems encountered in the detection process of the QRS complex of ECG. New Digital Filter is also a simple algorithm that makes the method fast and suitable in any real time application. Based on Exarchos et al. (Exarchos et al., 2007), a knowledge-based method for arrhythmic beat categorization and arrhythmic episode detection and categorization utilizing only the RR interval signal extracted from EKG recordings can also being done to get the highest accuracy in the EKG signal processing. The method is advantageous because the signal can be extracted with high accuracy even for noisy or complicated EKG recordings, while the extraction of all other EKG features or any other type of EKG analysis is seriously affected by noise and the processing time is reduced since only one feature is required compared to other methods that use more features or other types of EKG analysis.

The matched filter was used to detect dissimilar signal features of interest were the QRS Complex, the R-R intervals, and the ST segments on a human heart EKG signal. The matched filters will maximize the signal-to-noise ratio for a noisy signal so that the signal of interest that can be extracted. It is used to extract the ST segment which is the most considerable section to be extracted. The matched filter outputs were better than expected for the Normal and Long Term ST ECGs but for the Arrhythmia and Sudden Cardiac Death (Cardiac Arrest) ECGs, the results were not as good. Unfortunately, this method was not the case with the Arrhythmia and Cardiac Arrest ECGs when utilizing R-wave peak detection. The problem was because of the detection threshold used, not the matched filter implementation. The peak detection resolution was not sensitive enough to distinguish between the R-wave peaks and the ST segment peaks because of the use of a feature-length, sliding detection window. The use of QRS complex detection had much better results. The QRS complex matched filter detection with the Cardiac Arrest EKG was much better in detection, especially in the noisy areas where the R-wave peak matched filter failed. A better method for QRS complex detection along with R wave peak and ST segment detection would involve utilizing an adaptive filter to whiten the noise in the QRS complex. This method can be improved by utilizing dissimilar form of matched filter and better threshold detection, and then the matched filter EKG feature extraction could be made more successful (Y. Li, Tang, & Xu, 2015).

Research Concept

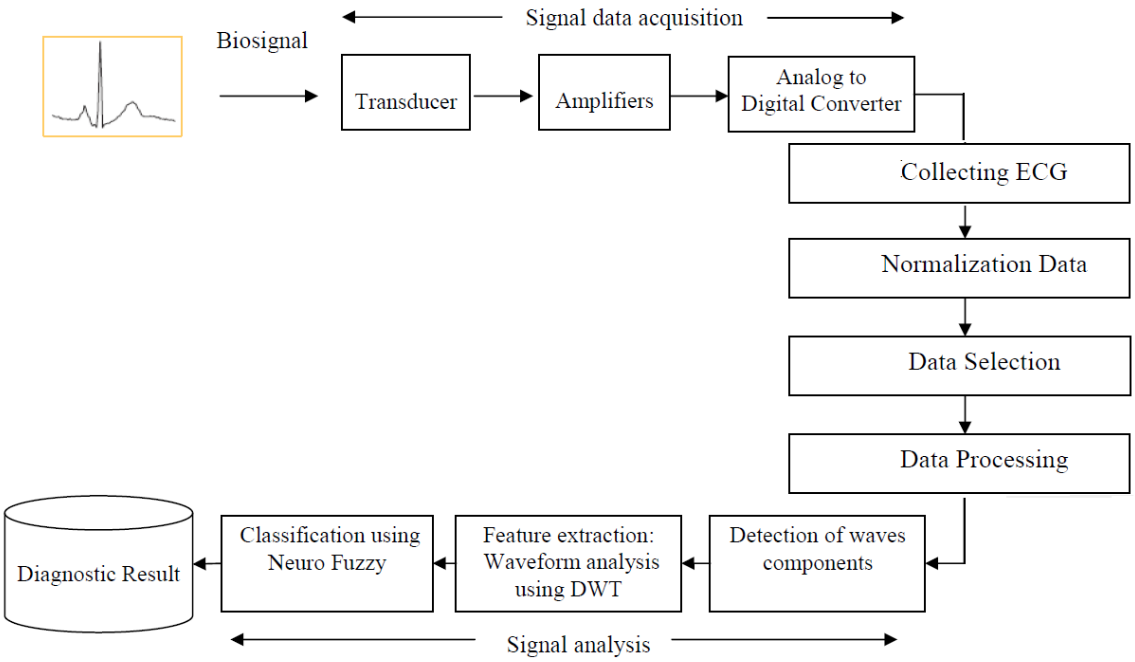


Figure 2.11 Illustration of study concept

Chapter 3
Research Methodology

Atrial Fibrillation Signals Dataset and Data Selection

The datasets with target outputs Class 1 (Normal), Class 2 (Abnormal level 1), Class 3 (Abnormal level 2) and Class 4 (Abnormal level 3) was given the target values of 1, 2, 3 and 4 respectively as shown in Figure 3.1 and Table 3.1. Based on Table 3.2, the EKG recordings consist of 276 subjects, 144 data samples were used for training and 132 data samples were used for testing. The samples belong to four categories: Normal, Bradycardia Arrhythmia, Tachycardia Arrhythmia and AFib (Presumably related to Ischemia).

Table 3.1 EKG signals class

The level of AFib risk	Class
Normal	1
Bradycardia	2
Tachycardia	3
AF	4

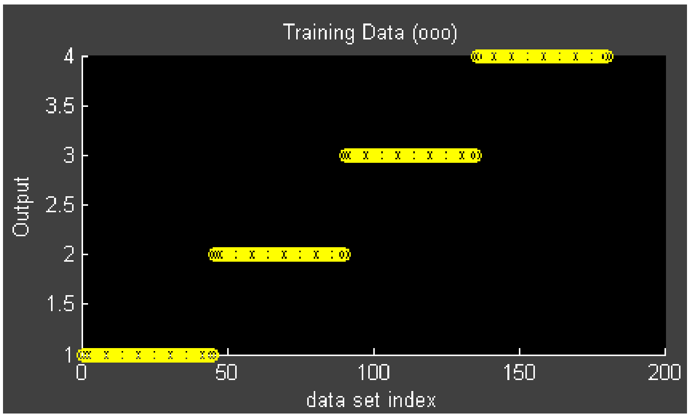


Figure 3.1 Desired output target for each class

Table 3.2 Sample data of each EKG signal

Signal	Class	Training set	Testing set	Total
Normal	1	36	32	68
Bradycardia	2	36	32	68
Tachycardia	3	36	34	70
AF	4	36	34	70
Total		**144**	**132**	**276**

Materials and instruments

The health of a population is a fundamental element contributing to progressive sustainable development in all regions of the world. Virtually all sciences contribute to the maintenance of human health and the practice of medicine. The development and implementation of science and technology in the medical application tools for instance, EKG will help to enhance the human healthcare and can assist people to check their health condition with fast and accurate. The invention of the new analysis method of medical instrumentation also can help to improve the efficiency and powerful medical applications.

The analysis of EKG is widely used for diagnosing many cardiac diseases that are the main cause of mortality in developed countries. Bio signal processing techniques for instance, EKG analysis system offer a powerful tool to simulate the human heart signal. The performance of such detection systems relies heavily on the accuracy and reliability in the detection of the signals that is necessary to determine the cardiovascular disease. The arrhythmia and AFib detection of EKG wave is a considerable topic.

This project is developed by utilizing numerical analysis software tool, the numerical computing environment and programming language software for modeling the heart signal in complex procedures. The AFINN were also used as classier tools in Fuzzy Logic Toolbox. Numerical analysis is a high-level language and interactive environment that enables to perform computationally intensive tasks faster than with traditional programming languages for instance, C, and C++. This software is among the most commonly used development languages. Numerical analysis codes also being used because it could read the raw data of EKG signal easily. The input EKG signal are imported from the data files .dat and also the excel file .xls.

In the previous EKG analysis research, numerous study and algorithm have been developed for the work of analyzing and classifying the EKG signal. The EKG analysis techniques are reviewed in and evaluate proposed methods of the categorization methods. The EKG analysis techniques have been identified and it required several stages.

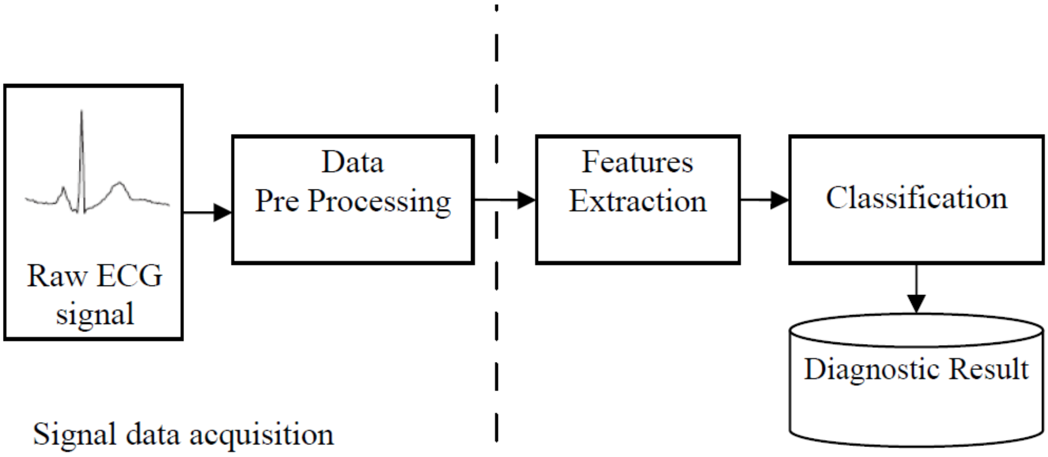


Figure 3.2 Electrocardiogram analysis

Electrocardiogram Analysis Method

The methods presented here are divided into three pieces of work. Firstly, procedures to identify and annotate of EKG signal for Normal, Bradycardia Arrhythmia, Tachycardia Arrhythmia and AFib characteristic. Secondly, a strategy is presented for extracting the features vector for each sample of selected cardiovascular disease utilizing an algorithm that exploits the coefficient derived from Discrete Wavelet Transform. Lastly, this part presented the procedures of categorization process utilizing Adaptive fuzzy inference neural network modeling.

Data Preparation

The EKG recording signals data are partitioning into cardiac cycles, and detection of the main events and intervals in each cycle have been done. The EKG signals which consist of P,Q,R,S and T wave have been detect based on their wave characteristic for instance, position, amplitude and intervals are shown in Table 3.1. The major features for instance, the QRS amplitude, R-R intervals, and wave's slope of EKG signal can be used as features to create the mapping structure are also identified.

Table 3.3 Main phases exist of electrocardiogram

Source	Section of Electrocardiogram
Record the electrical activity through the upper heart chambers (Atria Excitation)	P-Wave
Record the movement of electrical impulses through the lower heart chambers. (Atria repolarization + Ventricle depolarization)	QRS-Complex
Corresponds to the period when the lower heart chambers are relaxing electrically and preparing for their next muscle contraction. (Ventricle repolarization)	T- Wave
Corresponds to the time when the ventricle is contracting but no electricity is flowing through it.	ST segment

Data Characteristics

The characteristic for each sample of cardiovascular disease must be studied to make sure the characteristic is correct with the exact characteristics that have been identified by the doctor. The characteristics of each disease are described below.

AFIB template

- Inversion of T wave
- Decrease in amplitude or disappearance of R wave

- Shift of ST segment

Tachycardia Arrhythmia template

- Tachyarrhythmia are accelerated atrial or ventricular rates that exceed what is considered normal
- Beat too fast
- Regular
- Presence or absence of atrial depolarization (P wave, flutter waves).Diagnosis of cardiac arrhythmia cannot be considered complete without accounting for atrial activity.

Bradycardia Arrhythmia template

- Rhythms producing cardiac slowing are grouped together as Brady arrhythmias
- Beat too slow
- No P wave

The standard value of normal signal characteristics for Amplitudes and Durations of ECG Parameters are shown in Table 3.4 and Table 3.5 below.

Table 3.4 Amplitudes values of normal electrocardiogram signal

Wave	Amplitude(mV)
P	0.25
R	1.60
Q	0.40
T	0.1-0.5

Table 3.5 Normal electrocardiogram signal durations

Wave	**Duration** (sec)
P-R interval	0.12 - 0.20
Q - T interval	0.35 - 0.44
S-T segment	0.05 - 0.15
P wave interval	0.11
QRS interval	0.09

Data Acquisition and Preprocessing

Signal data acquisition is the first stage of record and capture data from the patient. Data files of the EKG recordings were imported into numerical analysis software where all computations were carried out. Initially, long sequences of data were processed to obtain the discrete wavelet transform of the entire recording of each subject. Figure 3.3 reveals the preprocessing step of EKG analysis.

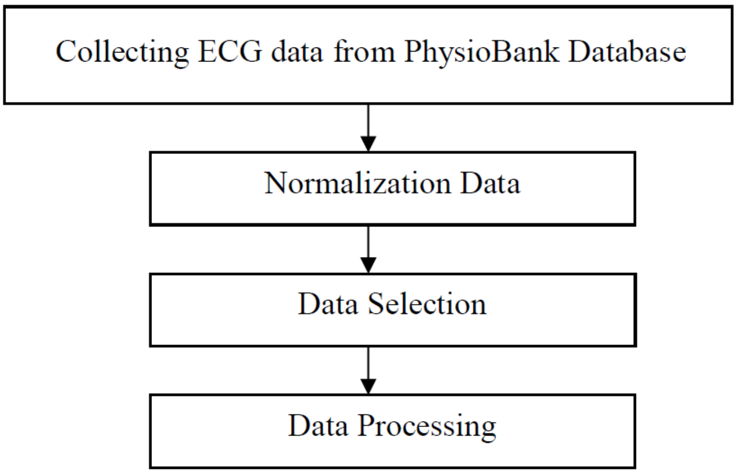


Figure 3.3 Preprocessing procedure

Data Sources and Normalization Data

The EKG signals were downloaded and recorded from the PhysioBank database utilizing MIT-BIH Arrhythmia Database and Intracardiac Atrial Fibrillation Database which are generally recognized as a standard test bench for the evaluation of arrhythmia detectors and basic study of cardiac dynamics.

When approaching data for modeling, some standard procedures should be used to prepare the data for modeling:

1. First the data should be filtered, and any outliers removed from the data

2. The data should be normalized or standardized to bring all of the variables into proportion with one another. For example, if one variable is 100 times larger than another (on average), then your model may be better behaved if you normalize/standardize the two variables to be approximately equivalent. Technically though, whether normalized/standardized, the coefficients related to each variable will scale appropriately to adjust for the disparity in the variable sizes. So anyway, if normalized/standardized, then the coefficients will reflect meaningful relative activity between each variable (i.e., a positive coefficient will mean that the variable acts positively towards the objective function, and vice versa, plus a large coefficient versus a small coefficient will reflect the degree to which that variable influences the objective function. Whereas the coefficients from un-normalized/un-standardized data will reflect the positive/negative contribution towards the objective function, but will bill much more difficult to interpret in terms of their relative impact on the objective function.

3. Non-numeric qualitative data should be converted to numeric quantitative data, and normalized/standardized. For example, if a survey question asked an interviewee to select where the economy will be for the next six months (i.e., deep recession, moderate recession, mild recession, neutral, mild recovery, moderate recovery, or strong recovery), these can be converted to numerical values of 1 through 7, and thus quantified for the model.

To normalize data, traditionally this means to fit the data within unity, so all data values will take on a value of 0 to 1. Since some models collapse at the value of zero, sometimes an arbitrary range of say 0.1 to 0.9 is chosen instead, but for this post

I will assume a unity-based normalization. The following equation is what should be used to implement a unity-based normalization:

$$x_{i,0\,1} = \frac{\delta_i - \delta_{\min}}{\delta_{\max} - \delta_{\min}}$$

where:

δ_i = each data point i

$\delta_{\max}$ = the maxima among all the data points

$\delta_{\min}$ = the minima among all the data points

$x_{i,0\,1}$ = the data point i normalized between 0 and +1

If you desire to have a more centralized set of normalized data, with zero being the central point, then the following equation can be used instead to normalize your data:

$$x_{i,-1+1} = \frac{\delta_i - \left(\frac{\delta_{\max} + \delta_{\min}}{2}\right)}{\left(\frac{\delta_{\max} - \delta_{\min}}{2}\right)}$$

where:

δ_i = each data point i

$\delta_{\max}$ = the maxima among all the data points

$\delta_{\min}$ = the minima among all the data points

$x_{i,-1+1}$ = the data point i normalized between -1 and +1

Finally, to standardize your data, you will want the data to reflect how many standard deviations from the average that that data lies, with the following normal distribution curve representing the probability of each standard deviation for a normal distribution (this graphic is borrowed from Wikipedia). The Z-Score is what will be calculated to standardize the data, and it reflects how many standard deviations from the average that the data point falls.

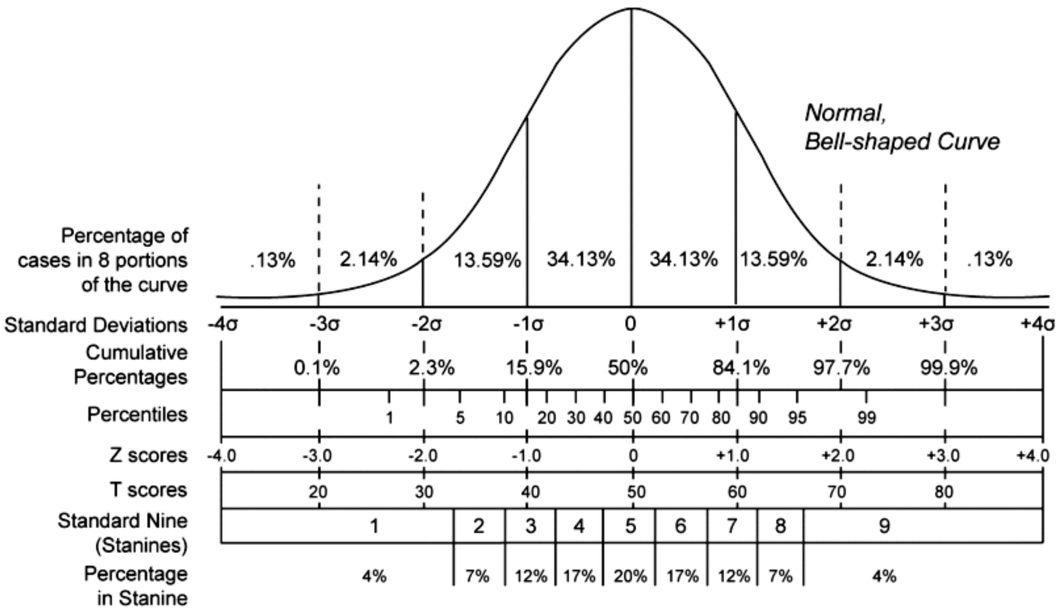


Figure 3.4 Illustration of normal distribution

To determine the Z-Score of each data point, the following equation should be used:

$$x_{i,1\sigma} = \frac{x_i - \overline{x}_s}{\sigma_{x,s}}$$

where:

$x_{i,1\sigma}$ = the data point i standardized to 1σ, also known as Z-Score

x_i = Each data point i

$\overline{x}_s$ = The average of all the sample data points

$\sigma_{x,s}$ = The sample standard deviation of all sample data point

Features Extraction Procedures

Feature extraction was conducted by applying wavelet analysis techniques to patient data, thus providing EKG characteristic point detection capabilities. Since most recently published detectors are based on standard database libraries and limited wave detection, this application is an attempt to expand the horizons of current study efforts. The input selection of feature extraction methods applied in this work has to select well to make sure which components of an inputs best represent the given pattern of EKG signals. Since the details wavelet coefficients contain a significant quantity of data about the signal, the detail wavelet coefficients of EKG signal of each subject were computed. The procedures of DWT implementation is describe as follow in**:**

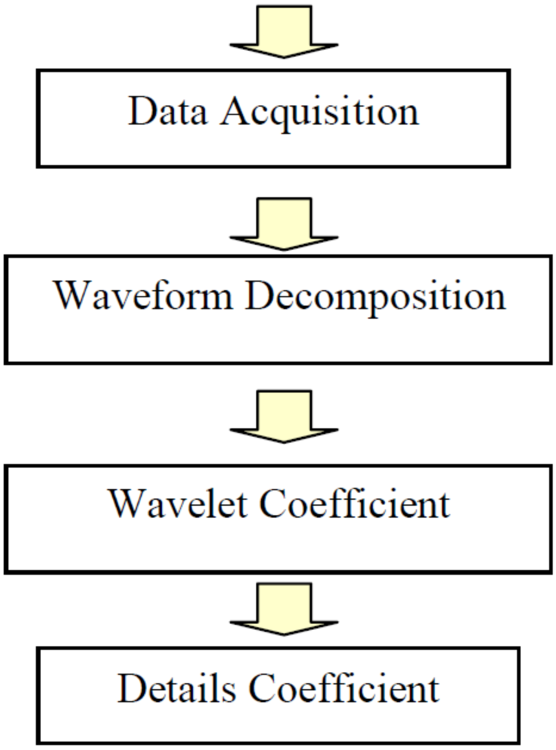


Figure 3.5 Feature extraction process

Selection of appropriate wavelet and the number of decomposition level is very considerable in DWT. The levels are chosen such that those parts of the signal that correlate well with the frequencies required for categorization of the signal are retained in the wavelet coefficients. The general wavelet decomposition of DWT scheme involves three steps. The result of decomposed signal will reveals the considerable details and approximation coefficients which represent the original signal. The basic version of the scheme follows the steps described below.

- select a wavelet types.
- select a wavelet name.
- select a level *N* which will compute the wavelet decomposition of the signal *s* at level *N*.

The DWT wavelet types have been chosen in this features extraction method and the EKG signals were decomposed into time-frequency representations utilizing single-level one-dimensional wavelet decomposition. The wavelet names of Daubechies wavelet filters db4 have been choosing and the number of decomposition levels was chosen to be 5. Thus, the EKG signals were decomposed into the details coefficients D1-D5 and one final approximation coefficient, A5.

The result of applying the Daubechies wavelet of order 4 (db4) which is more suitable to detect changes of EKG signal is evaluated. The wavelet filter with scaling function more closely similar to the shape of the EKG signal achieved better detection. Db wavelet family is similar in shape to EKG signal and their energy spectrums are concentrated around low frequencies the signal is approximated by omitting the signals high frequency components. The EKG signal and the details for five wavelet scales are schematically shown for better illustration in Figure 3.6.

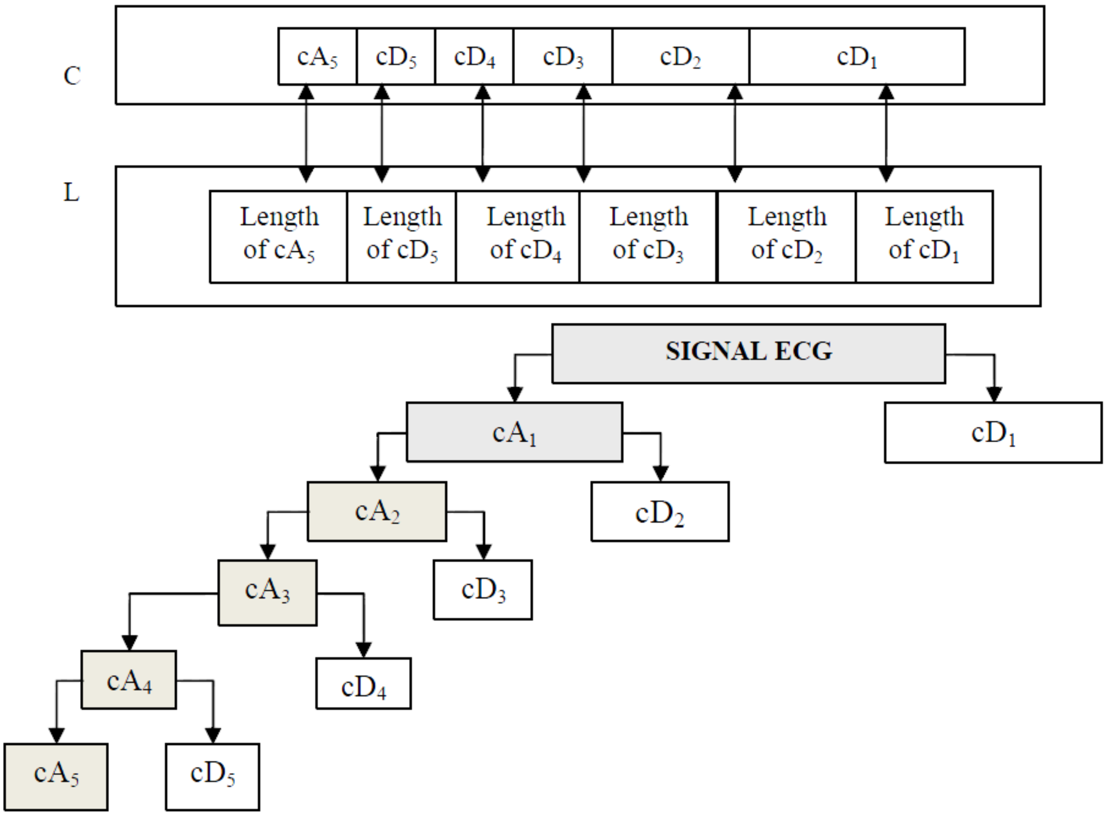


Figure 3.6 DWT decomposition step in EKG analysis

Coefficients Extraction

The calculated wavelet coefficients provide a compact representation that reveals the energy distribution of the signal in time and frequency. Therefore, the calculated details and approximation wavelet coefficients of the EKG signal were used as the features vector representing the signals. From the original intervals of EKG signal, five standard measures parameters used are used. A signal of 75 discrete data was selected as considered EKG signals data. For each EKG signals, the detail wavelet coefficients of fourth level (75 coefficients) were computed. In order to reduce the dimensionality of feature vectors, statistics over the set of the wavelet coefficients were used. The following statistical features were used to represent the time–frequency distribution of the EKG signals: The flows of the calculated DWT coefficient are shown in Figure 3.7 below.

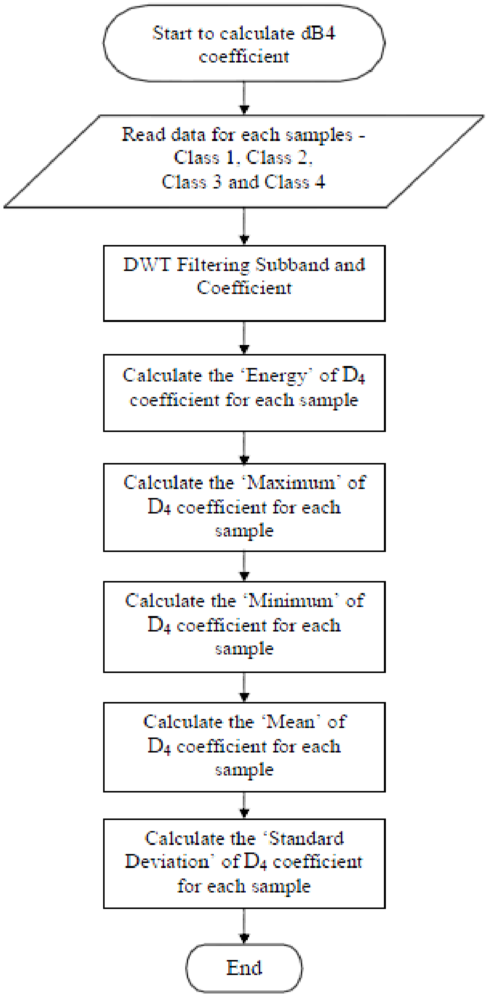


Figure 3.7 Flowchart of DWT coefficient calculation

1. Energy of the wavelet coefficients of each EKG signals sample.
2. Maximum of the wavelet coefficients of each EKG signals sample.
3. Minimum of the wavelet coefficients of each EKG signals sample.
4. Mean of the wavelet coefficients of each EKG signals sample.
5. Standard deviation of the wavelet coefficients of each EKG signals sample.

The sub band 4, D4 of details coefficients from the wavelet decomposition structure has been extracted. These vectors are extracted at each scale without scale one, two and three. It is ignoring the higher levels of decomposition because it contains high frequency details and noise. These details are insignificant data that will not affect the categorization accuracy and signal quality. This implies that it is likely to delete data of very small magnitude in each subspace, resulting in much less data data being needed to reconstruct a very good approximation of the original signal. Then, the output of the detail coefficients extracted from the signal will be defined as the input of AFINN classifier as systematically shown in Figure 3.8.

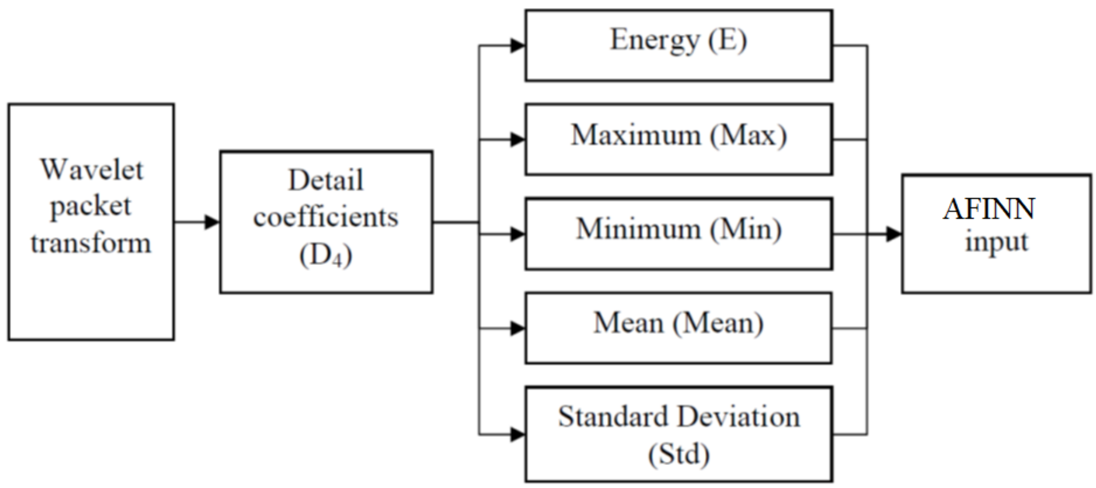


Figure 3.8 The coefficients extracted and AFINN classifier analysis framework

Performance Evaluation Method

The AFib detectors are compared on the base of the following performance metrics:

- Sensitivity:

$$Se\ (\%) = \frac{TP}{TP + FN} x100\%$$

- Specificity:

$$Sp(\%) = \frac{TN}{TN + FP} x100\%$$

- Accuracy:

$$Acc(\%) = \frac{TP + TN}{N} x100\%$$

- Positive Predictive Value:

$$PPV\ (\%) = \frac{TP}{TP + FP} x100\%$$

- Negative Predictive Value:

$$NPV\ (\%) = \frac{TN}{TN + FN} x100\%$$

- Total error:

$$Err\ (\%) = \frac{FP + FN}{N} x100\%$$

where TP is the number of True Positive, TN is the number of True Negative, FP is the number of False Positive, FN is the number of False Negative and N is the total number of observations.

Chapter 4

Results

Characteristic Properties and Rule Base Identification

The characteristic properties of the raw data are presented in Table 4.1. There are five features that represent the EKG signals were used by AFINN classifiers to predict the Normal, Bradycardia Arrhythmia, Tachycardia Arrhythmia and AF.

Table 4.1 Statistic properties of the datasets

Characteristic	Class 1	Class 2	Class 3	Class 4
Energy	2.1403	0.0179	6.9619	0.0146
Maximum	2.2859	0.5251	2.9569	0.669
Minimum	-2.8638	-1.1435	-2.3872	-0.9561
Mean	-0.0094	-0.00457	0.0611	-0.0118
SD	0.5737	0.1477	0.8639	0.2376

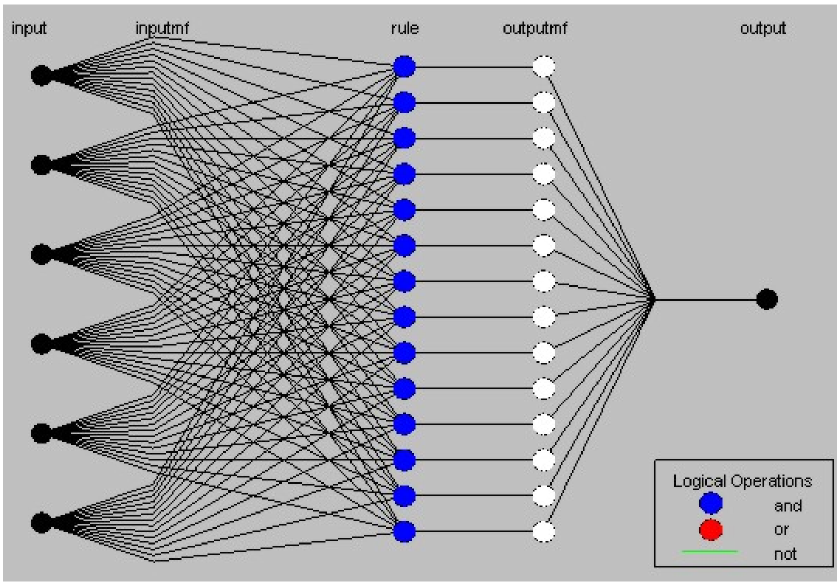


Figure 4.1 Rule-based AFINN structure

Table 4.2 Created rule base by expert knowledge

Rule	Feature					Class
	Energy	Maximum	Minimum	Mean	SD	
1	M	M	S	M	L	1
2	M	M	M	M	L	1
3	L	M	S	M	L	1
4	S	S	M	M	S	2
5	S	S	M	M	S	2
6	S	M	M	L	S	2
7	L	L	S	L	L	3
8	L	L	M	L	L	3
9	L	M	M	L	L	3
10	S	S	L	S	M	4
11	S	S	M	S	M	4
12	M	S	L	S	M	4

*S=small, M=medium, L=large

Preprocessing Result

The Figure 4.2 displays below represent the preprocessing process for each sample of dataset which are Normal, Bradycardia Arrhythmia, Tachycardia Arrhythmia and AFib. It is consist of original signal before processing and the detail wavelet coefficients of Discrete Wavelet Transform.

Normal Signal

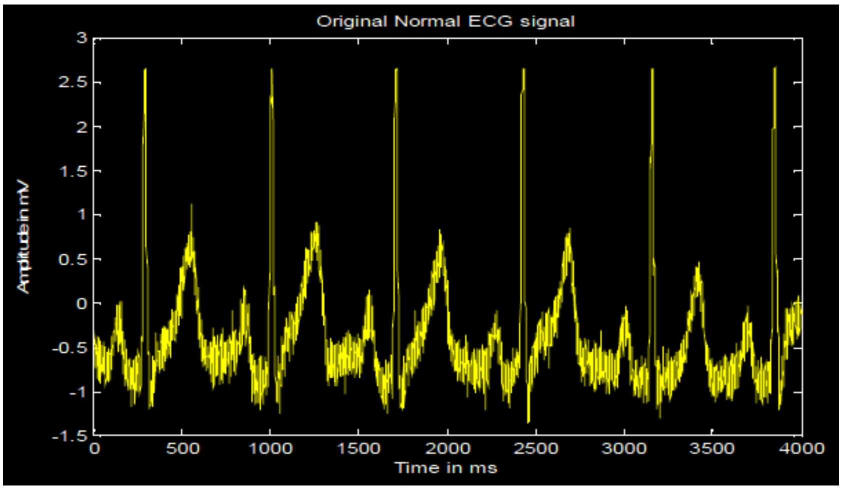


Figure 4.2 Normal EKG signal

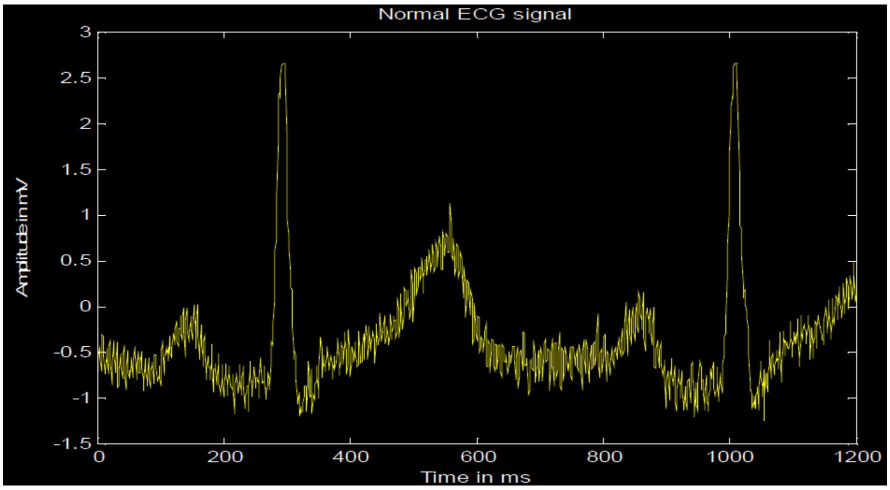


Figure 4.3 Illustration of the normalized normal EKG signal

Figure 4.2 and 4.3 reveal the original data of Normal EKG signal, the design for wavelet analysis were formed by first 1200 packets data, the collected data are shown in Figure 4.3. This provides a meaningful data for processing in defining detail wavelet coefficients of Normalized Normal EKG signals. Figure 4.4 reveal the frequency component for first 1200 data processing of the Normal EKG signal.

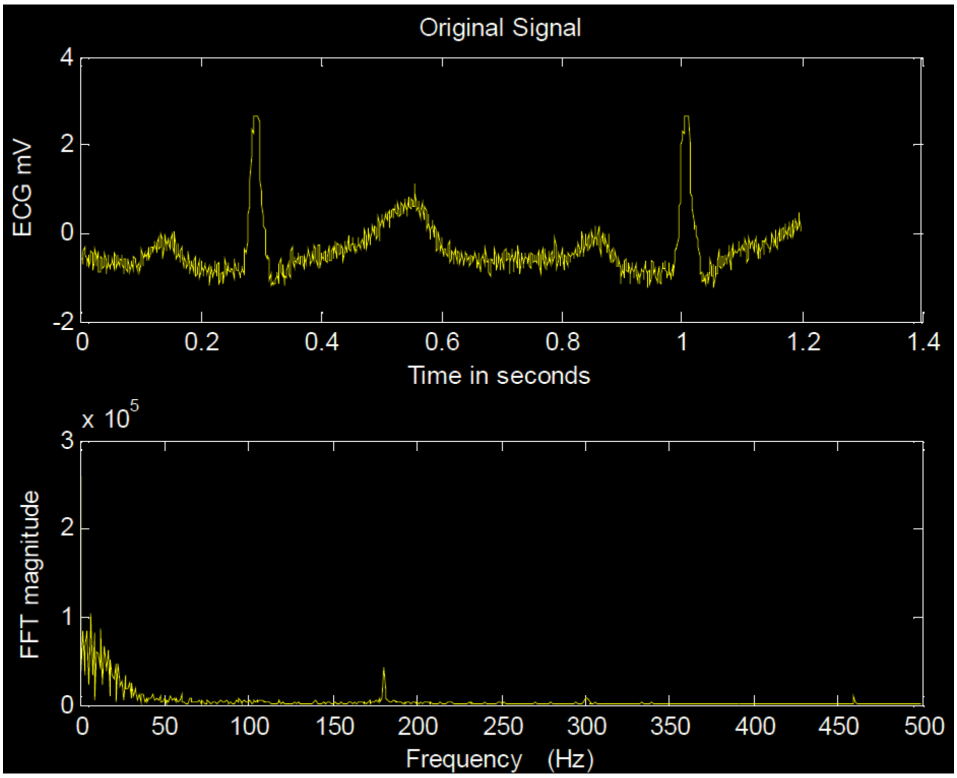


Figure 4.4 Frequency domain of normal EKG signal

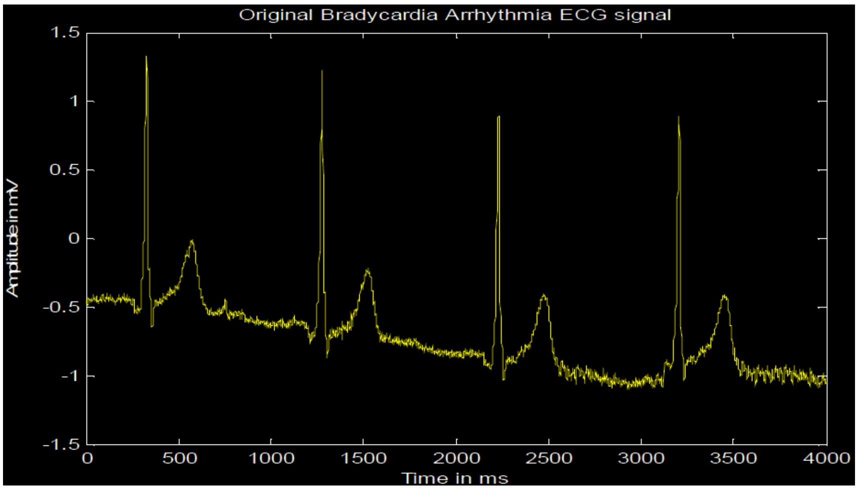


Figure 4.5 Bradycardia arrhythmia EKG signal

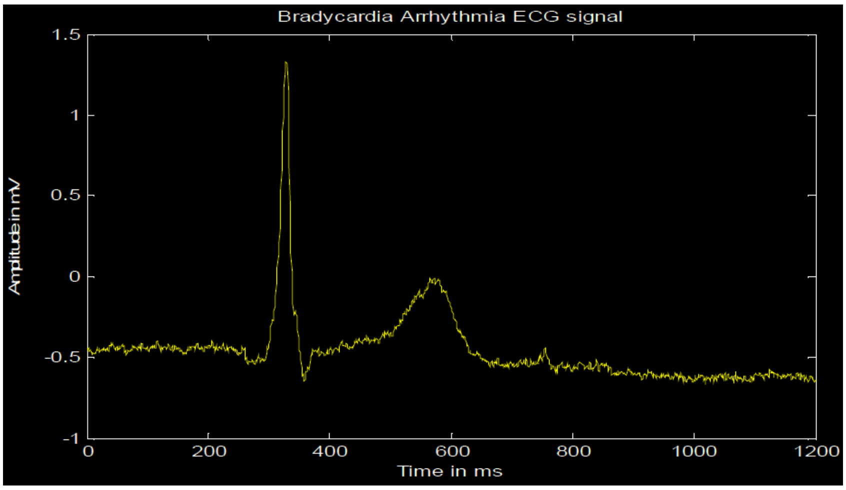


Figure 4.6 Illustration of normalized bradycardia arrhythmia EKG signal

Figure 4.5 and 4.6 reveal the original data of Bradycardia Arrhythmia EKG signal, the design for wavelet analysis were formed by first 1200 packets data, the collected data are shown in Figure 4.6. This provides a meaningful data for processing in defining detail wavelet coefficients of Normalized Bradycardia Arrhythmia EKG signals.

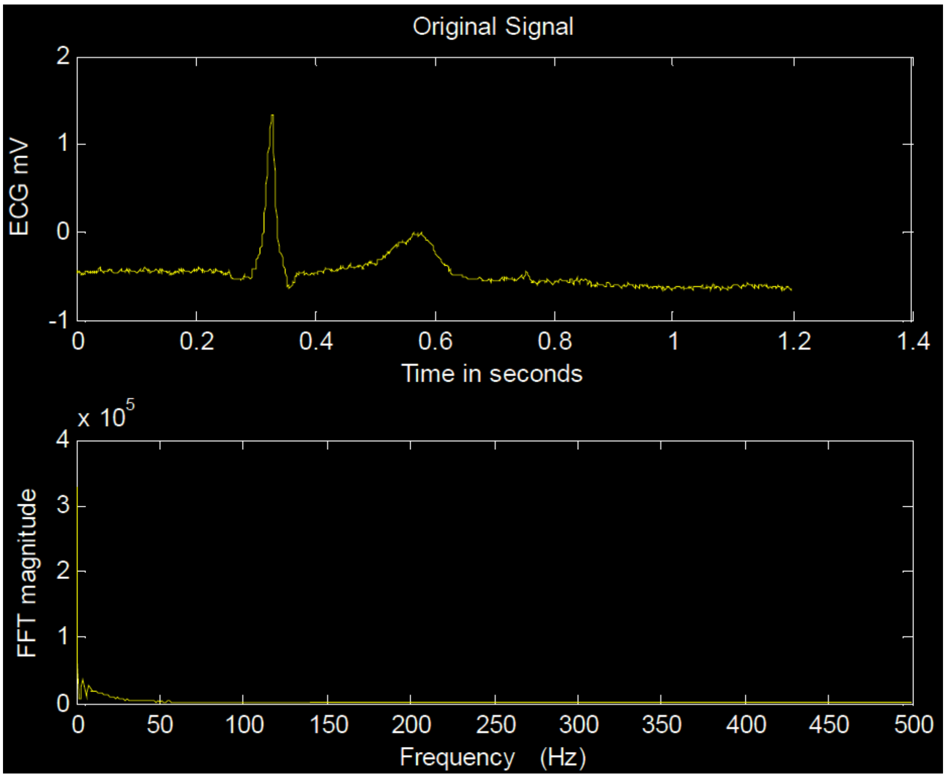


Figure 4.7 Frequency component of bradycardia arrhythmia EKG signal

Figure 4.7 reveal the frequency component for first 1200 data processing of the Bradycardia Arrhythmia EKG signals.

Tachycardia Arrhythmia Signal

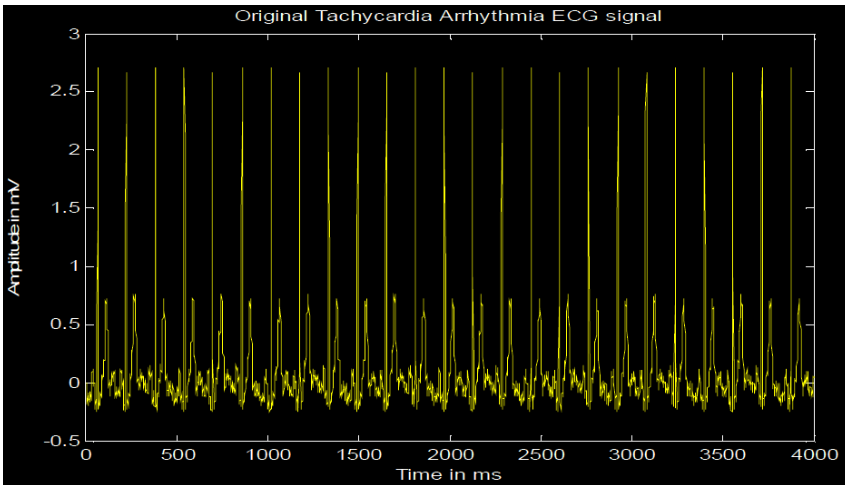


Figure 4.8 Tachycardia arrhythmia EKG signal

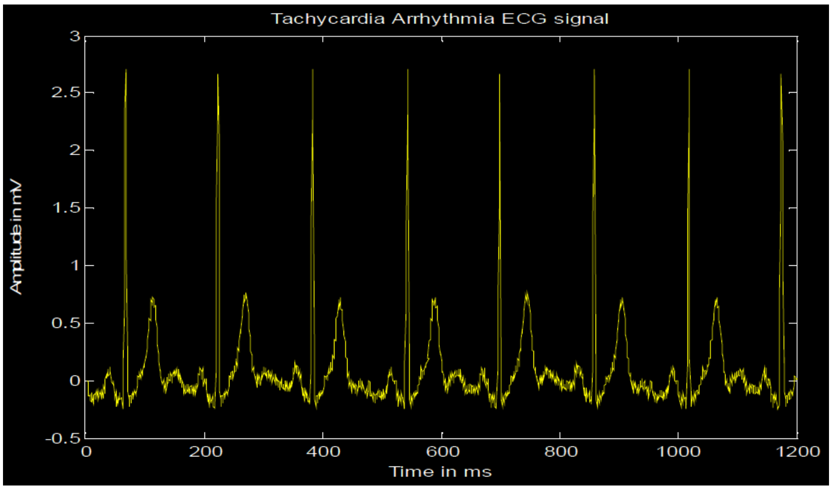


Figure 4.9 Illustration of normalized tachycardia arrhythmia EKG signal

Figure 4.8 and 4.9 reveal the original data of Tachycardia Arrhythmia EKG signal, the design for wavelet analysis were formed by first 1200 packets data, the collected data are shown in Figure 4.9. This provides a meaningful data for processing in defining detail wavelet coefficients of Tachycardia Arrhythmia EKG signals.

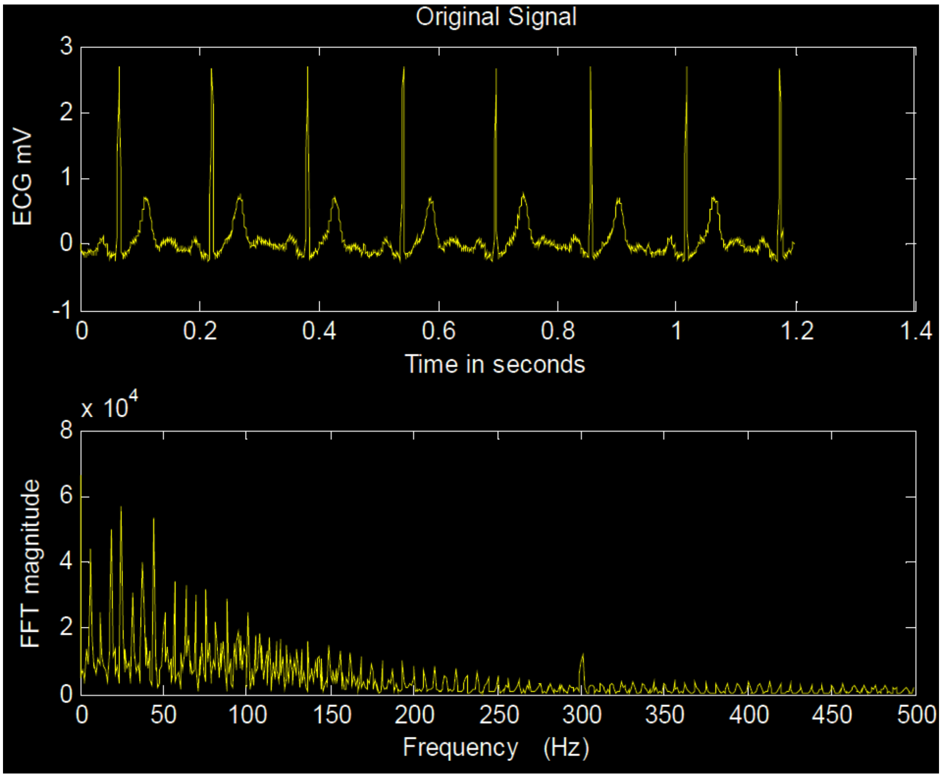


Figure 4.10 Frequency component of tachycardia arrhythmia EKG signal

Figure 4.10 reveal the frequency component for first 1200 data processing of the Tachycardia Arrhythmia EKG signal.

AFIB Signal

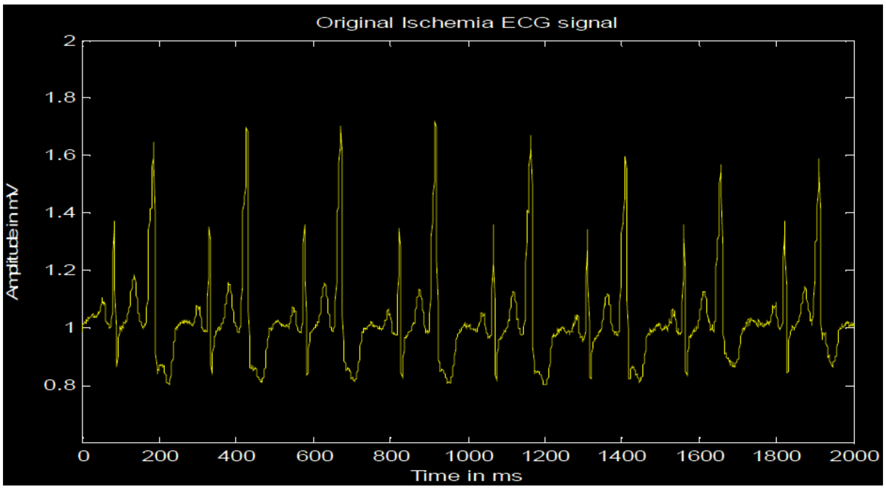


Figure 4.11 AFib EKG signal

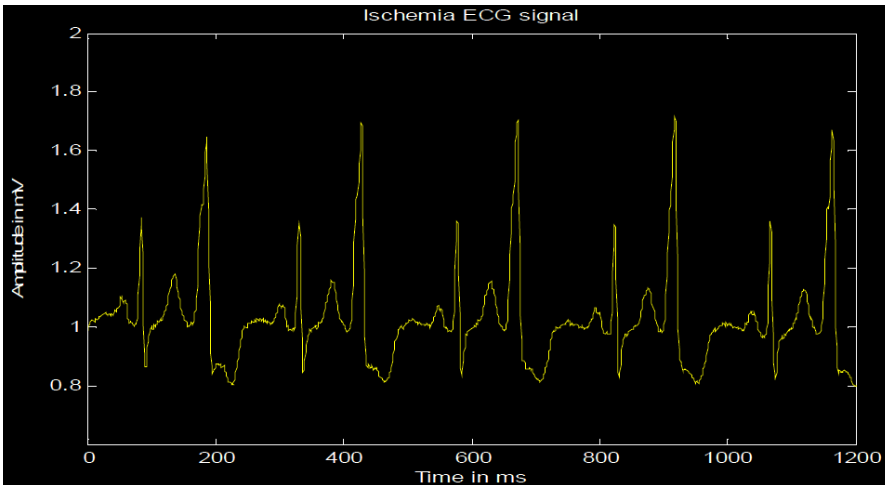


Figure 4.12 Illustration of normalized AFib EKG signal

Figure 4.11 and 4.12 reveal the original data of AFib EKG signal, the design for wavelet analysis were formed by first 1200 packets data, the collected data are shown in Figure 4.12. This provides a meaningful data for processing in defining detail wavelet coefficients of AFib EKG signals.

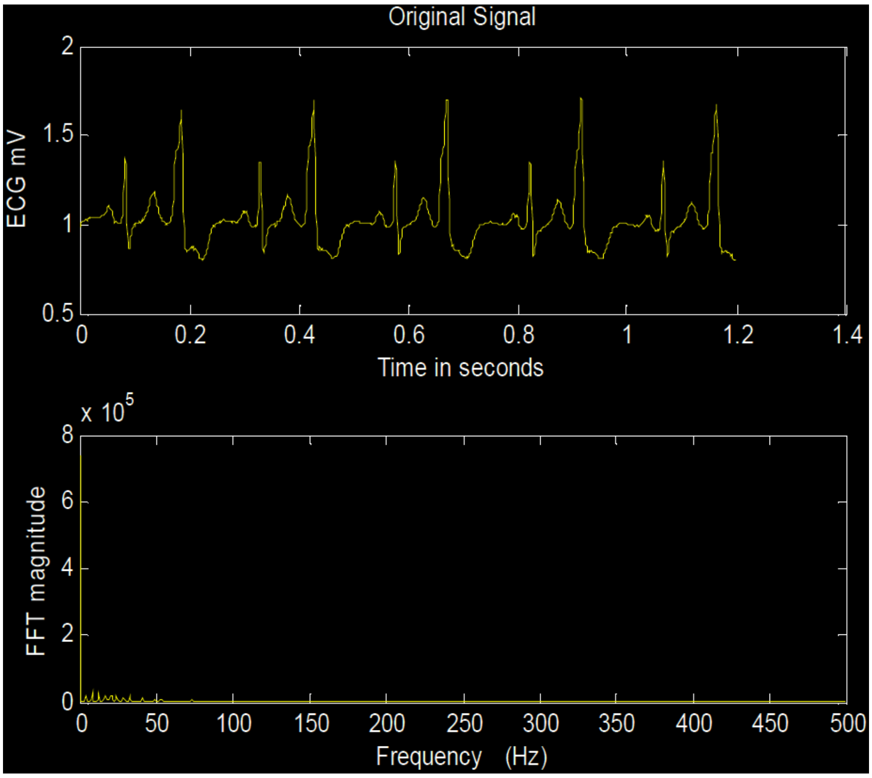


Figure 4.13 Frequency component of AFib EKG signal

Figure 4.13 reveal the frequency component for first 1200 data processing of the AFib EKG signal.

Features Extraction Result

The figures below reveal the overall process of DWT decomposition of each signal.

Normal Signal

Figure 4.14 reveal the vector coefficient and the length of the Normal signal for 1200 data processing. Figure 4.15 reveal the approximation and detail coefficient for the level 1 DWT decomposition of Normal signal. The filtering process of detail coefficient of level 1 is continued until the desired level up to 5 levels is reached.

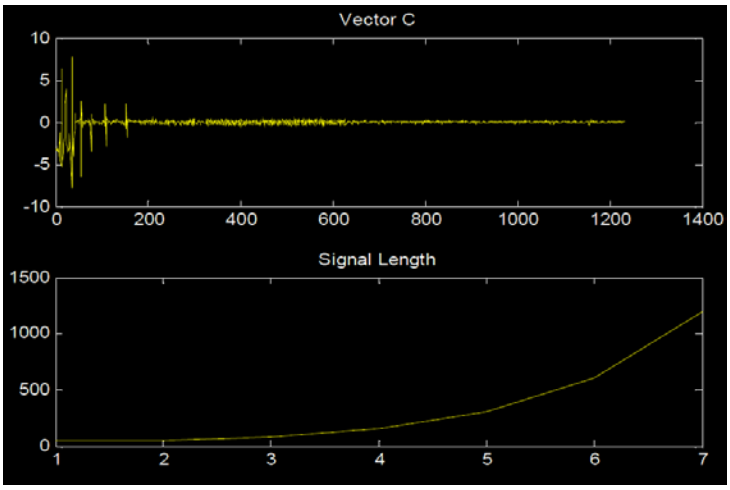


Figure 4.14 The vector, C and length, L of normal signal

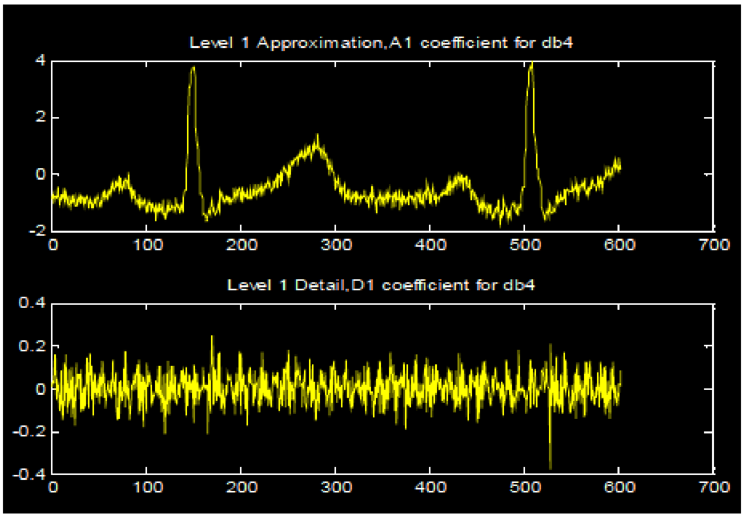


Figure 4.15 The approximation, A and detail, D coefficients of level 1 decomposition

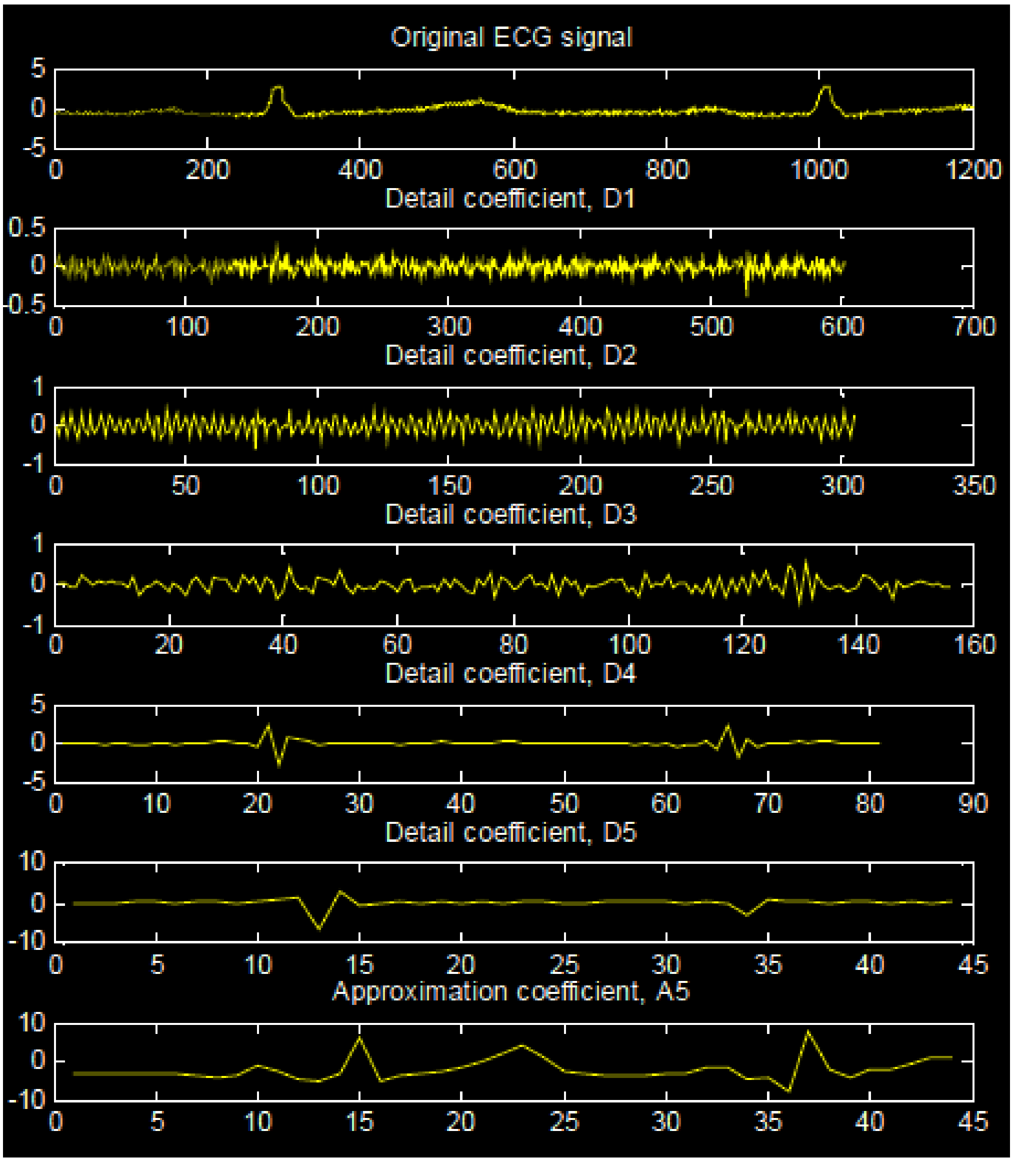


Figure 4.16 The detail coefficients of D_1 to D_5 and approximation coefficient of A_5

Bradycardia Arrhythmia Signal

Figure 4.17 reveal the vector coefficient and the length of the Bradycardia Arrhythmia signal for 1200 data processing. Figure 4.18 reveal the approximation and detail coefficient for the level 1 DWT decomposition of Bradycardia Arrhythmia signal. The filtering process of detail coefficient of level 1 is continued until the desired level up to 5 levels is reached.

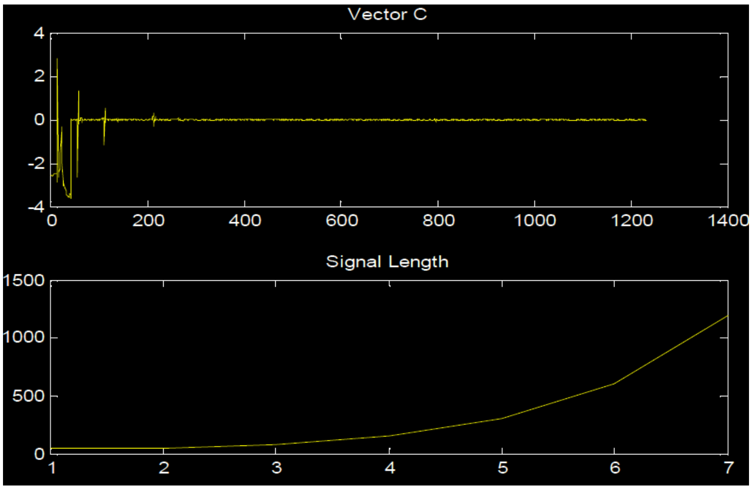


Figure 4.17 The vector, C and length, L of bradycardia arrhythmia signal

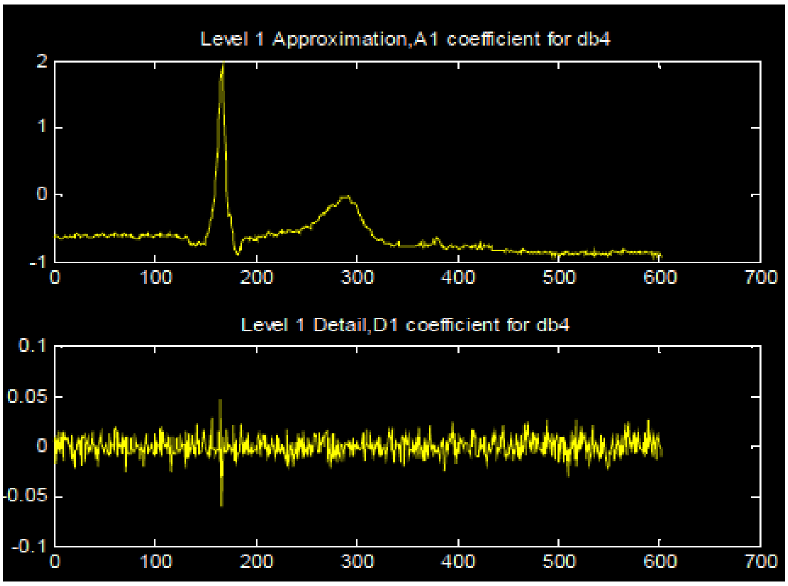


Figure 4.18 The approximation, A and detail, D coefficients of level 1 decomposition

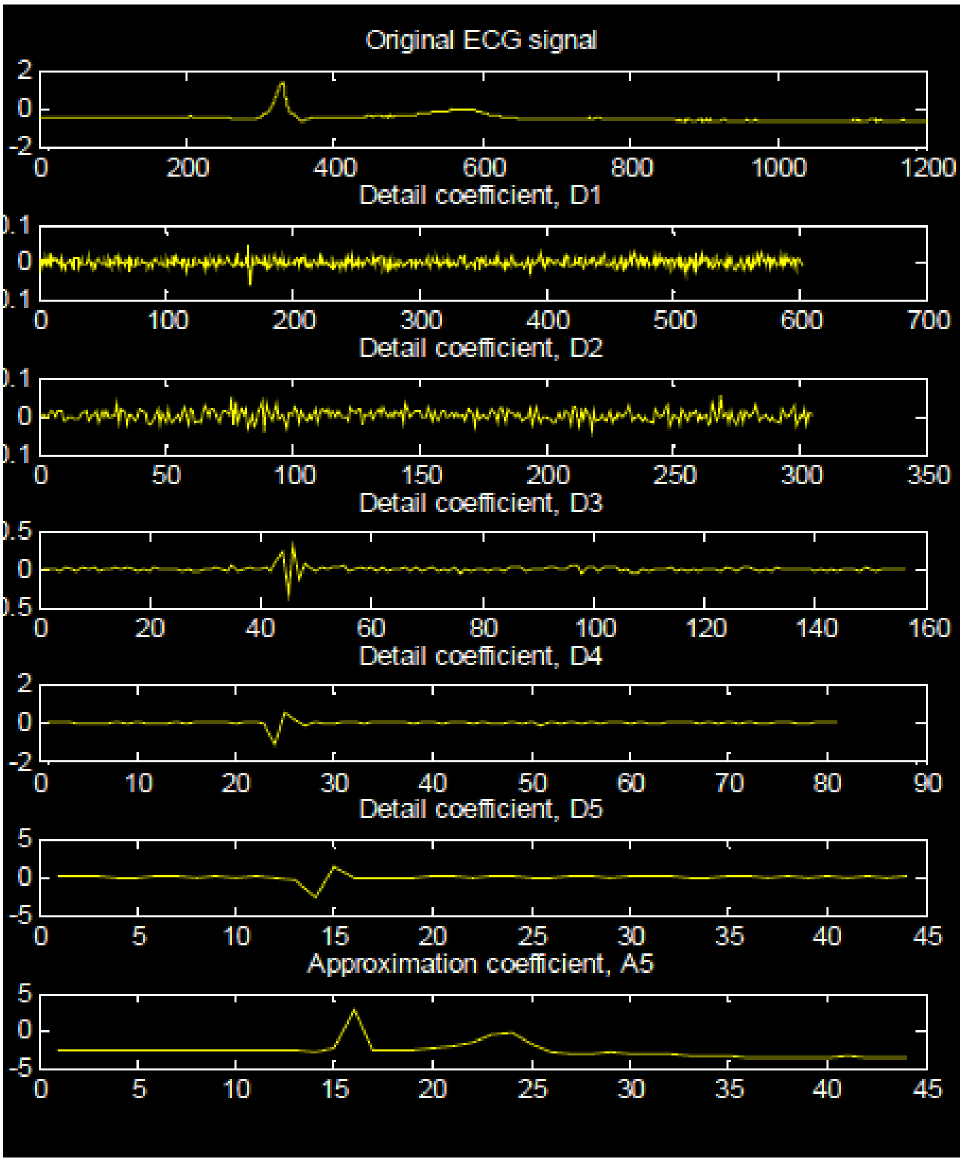


Figure 4.19 The detail coefficients of D_1 to D_5 and approximation coefficient of A_5

Figure 4.19 reveal the original Bradycardia Arrhythmia EKG signals and detail coefficients of each level and also approximation coefficient of A5. These wavelet coefficients were used as AFINN inputs.

Tachycardia Arrhythmia Signal

Figure 4.20 reveal the vector coefficient and the length of the Tachycardia Arrhythmia signal for 1200 data processing. Figure 4.21 reveal the approximation and detail coefficient for the level 1 DWT decomposition of Tachycardia Arrhythmia signal. The filtering process of detail coefficient of level 1 is continued until the desired level up to 5 levels is reached. Figure 4.22 reveal the original Tachycardia Arrhythmia EKG signals and detail coefficients of each level and also approximation coefficient of A5. These wavelet coefficients were used as AFINN inputs.

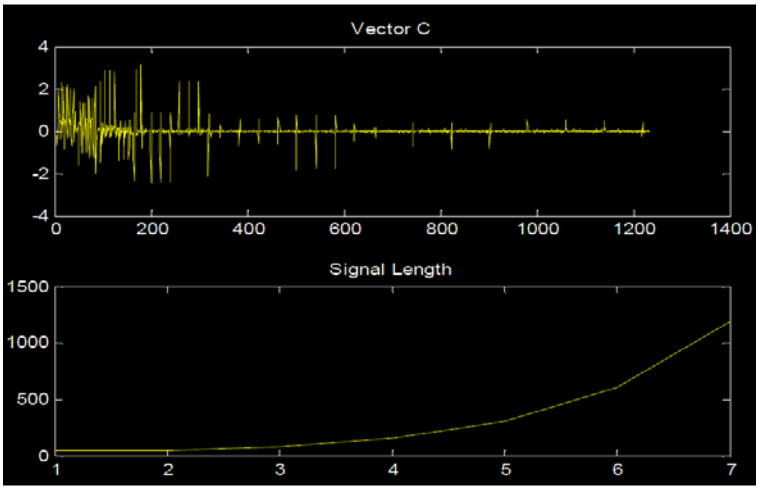


Figure 4.20 The vector, C and length, L of tachycardia arrhythmia signal

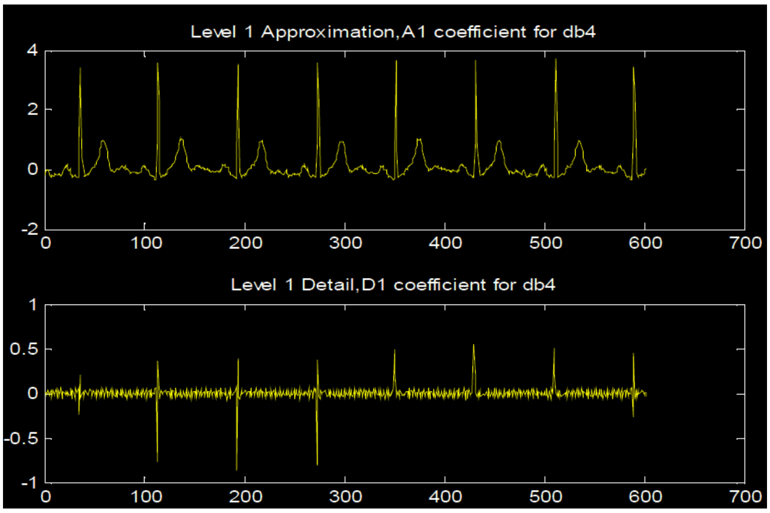


Figure 4.21 The approximation, A and detail, D coefficients of Level 1 decomposition

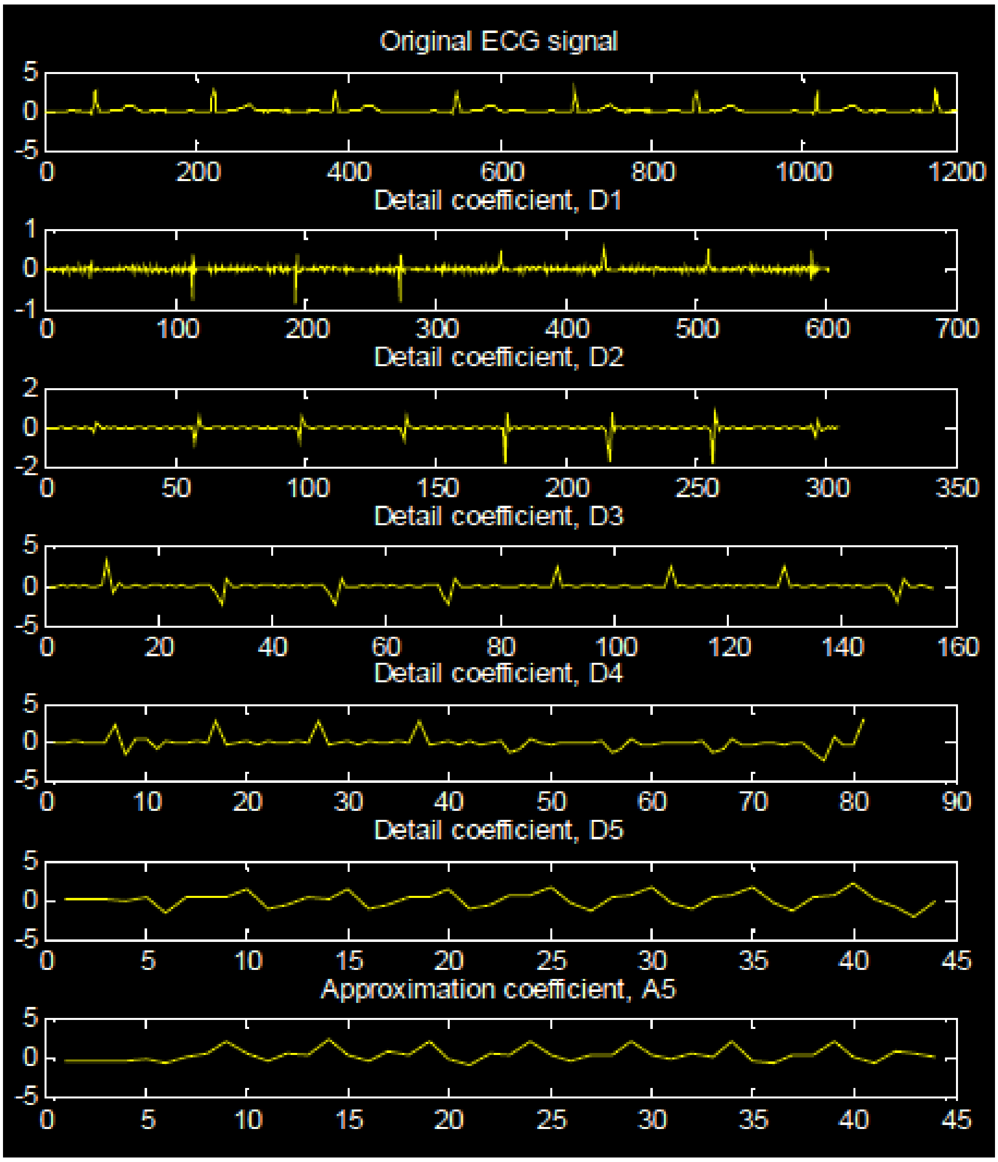


Figure 4.22 The Detail coefficients of D_1 to D_5 and Approximation coefficient of A_5

AFib Signal

Figure 4.23 reveal the vector coefficient and the length of the AFib signal for 1200 data processing. Figure 4.24 reveal the approximation and detail coefficient for the level 1 DWT decomposition of AFib signal. The filtering process of detail coefficient of level 1 is continued until the desired level up to 5 levels is reached.

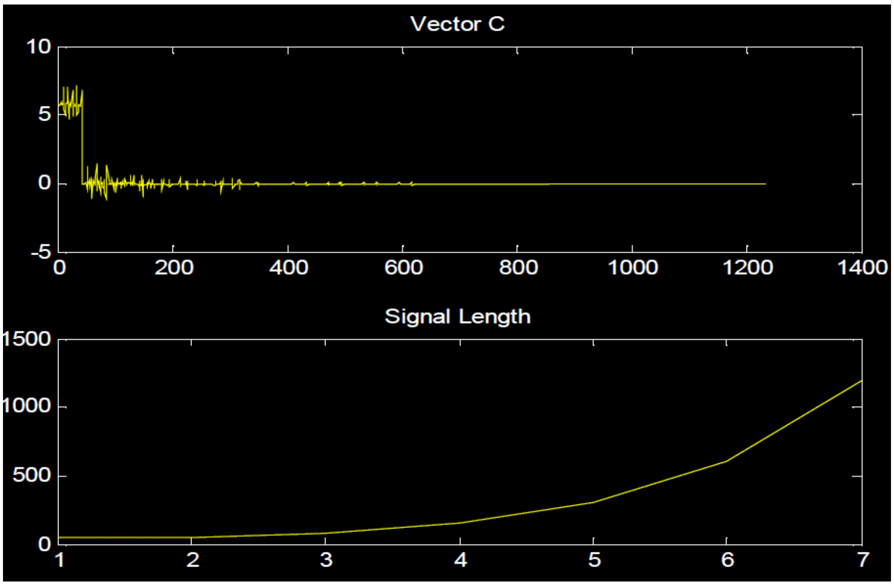


Figure 4.23 The vector, C and length, L of AFib signal

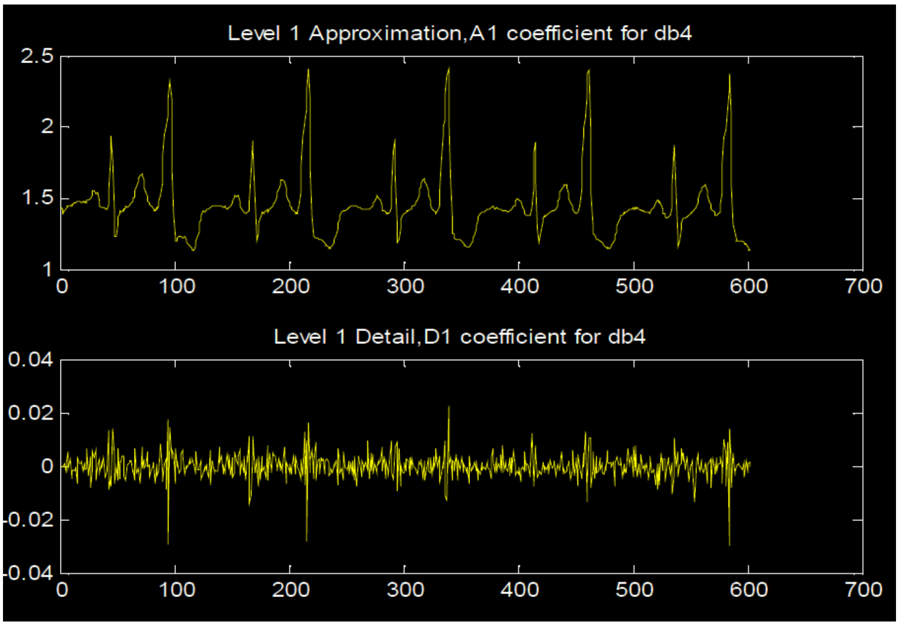


Figure 4.24 The approximation, A and detail, D coefficients of level 1 decomposition

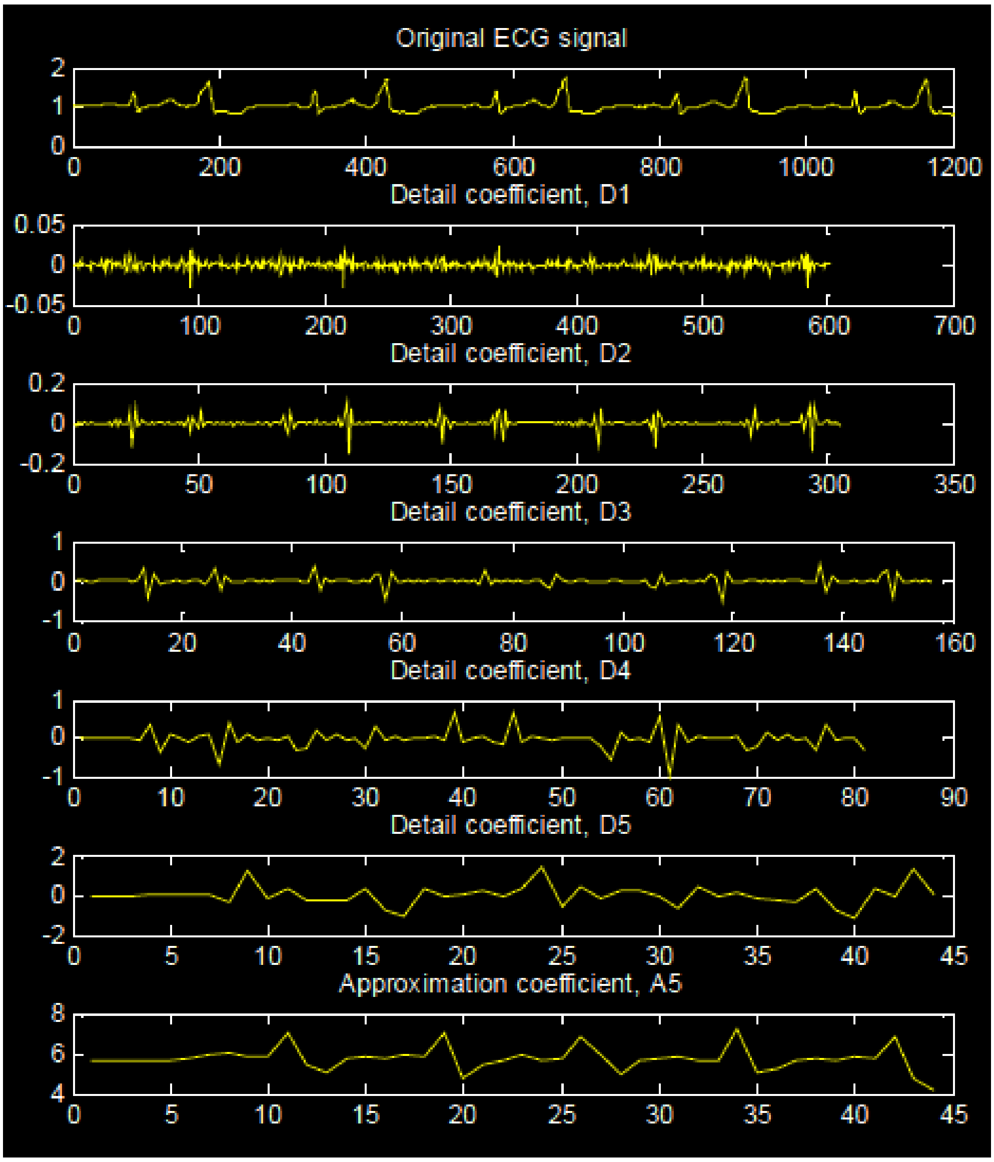


Figure 4.25 The detail coefficients of D_1 to D_5 and approximation coefficient of A_5

Figure 4.25 reveal the original AFib EKG signals and detail coefficients of each level and also approximation coefficient of A_5. These wavelet coefficients were used as AFINN inputs.

Featured Vector of Discrete Wavelet Transform

From the Table 4.3, the 20 extracted features vectors of four classes of EKG signal which were calculated from the D_4 frequency band was reveals the dissimilar from each other, therefore, it is useful parameters in classifying the EKG signals.

Table 4.3 The features of exemplary records from each classes

Dataset	Features	DWT Coefficient
Normal beat	Energy	2.14
	Maximum	2.29
	Minimum	-2.86
	Mean	-0.01
	SD	0.57
Bradycardia Arrhythmia	Energy	0.02
	Maximum	0.53
	Minimum	-1.14
	Mean	0.00
	SD	0.15
Tachycardia Arrhythmia	Energy	6.96
	Maximum	2.96
	Minimum	-2.39
	Mean	0.06
	SD	0.86
AF	Energy	0.01
	Maximum	0.67
	Minimum	-0.96
	Mean	-0.01
	SD	0.24

The DWT features coefficient extracted from each EKG signal showing the dissimilar value for all samples for the training and testing datasets. All of the features coefficients were used by AFINN as classifier input.

Adaptive fuzzy inference neural network categorization Result

The categorization of the EKG signals utilizing the combination of DWT features coefficients and AFINN that was trained with the back propagation gradient descent method in combination with the least squares method has been made. The hybrid algorithm is composed of a forward pass and a backward pass. The least squares method (forward pass) is used to optimize the consequent parameters with the premise parameters fixed. Once the optimal consequent parameters are found, the backward pass starts immediately. The gradient descent method (backward pass) is used to adjust optimally the premise parameters corresponding to the fuzzy sets in the input domain. The output of the AFINN is calculated by employing the consequent parameters found in the forward pass. The output error is used to adapt the premise parameters by means of a standard back propagation algorithm.

The present study demonstrated that the wavelet coefficients are the features which will represent the EKG signals and the AFINN trained on these features achieved high categorization accuracies. In classification, the aim is to assign the input patterns to one of four classes, usually represented by outputs restricted to lie in the range from 1 to 4, so that they represent the probability of the class membership. While the categorization is carried out, the specific pattern is assigned to specific class according to the characteristic features that represent the EKG signal.

In this study, training and test sets were formed by 352 data samples. The 180 data samples were used for training and 172 data samples were used for testing. The training dataset was used to train the AFINN, whereas the testing dataset was used to verify the accuracy and the effectiveness of the trained AFINN model for the detection of cardiovascular disease patients. The steps of parameter adaptation of the AFINN are shown in Figure 4.26.

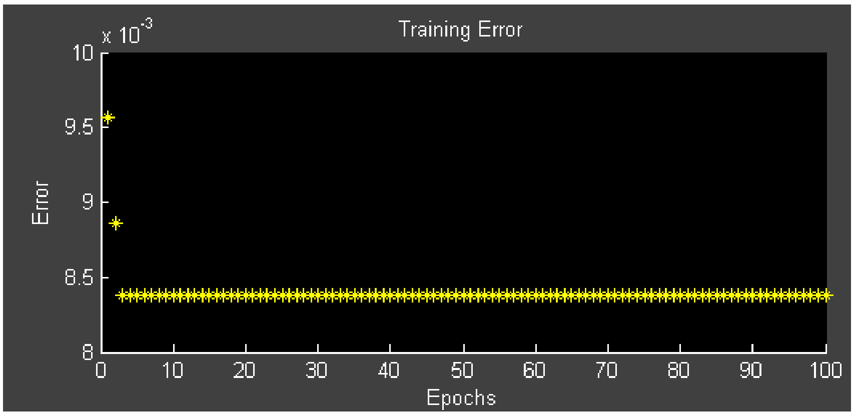


Figure 4.26 AFINN network error convergence

Based on the Figure 4.26, the AFINN used 180 training data in 100 training periods and the step size for parameter adaptation had an initial value of 0.011. At the end of 100 training periods, the network error convergence curve of AFINN had the final error convergence value which is 0.0083787. Figure 4.27 below reveals the plot for 243- rule base AFINN training performance. This system reveals it is sufficient to get zero training error since there are 243 rules trying to classify 180 data samples.

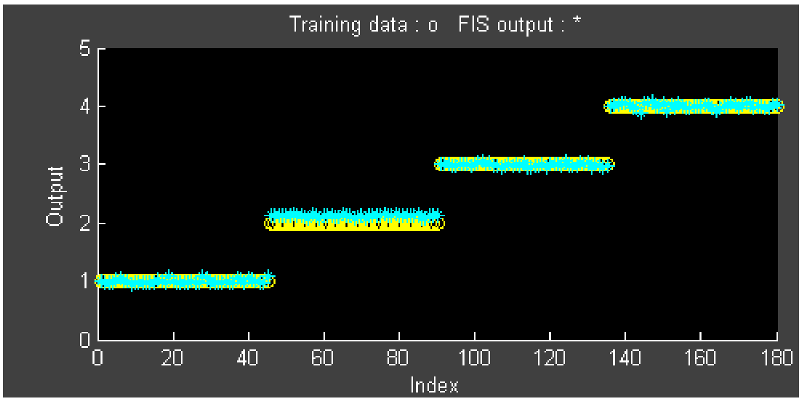


Figure 4.27 Plot for Rule-based AFINN training performance

The green points represent in the figure is calculated output from the AFINN structure while the yellow points are desired target for 180 training data. The figure also reveals the small errors occurs for Class 2 whose the calculated output not lies precisely in the Class 2, whereas the other calculated output strictly tied to their class desired output. But, the errors spotted around Class 2 data samples still not across the decision boundary of 2.5, so it is still classify as Class 2. Then, after training, 172 testing data was used to validate the accuracy of the AFINN classifier for the detection of EKG signals. The Figure 4.28 reveals the result of AFINN model testing performance.

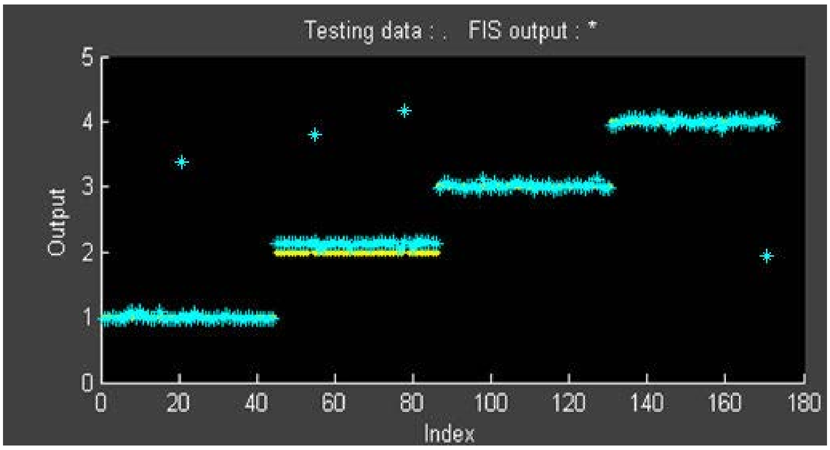


Figure 4.28 AFINN model testing performance

The testing data distribution in Figure 4.28 reveals that there are small errors occurs in classifying the cardiovascular disease since the average testing error is 0.31715. One error is spotted around the 20th sample whose value is above 1.5, that is across the decision boundary and misclassified as Class 3. Two errors occur from Class 2 that spotted around the 60ttth and 80th samples of the class which are misclassified as Class 4. One error occurs from Class 4 since the data sample was classified as Class 2.

The categorization results of the AFINN model for 172 testing data were displayed in Table 4.4, Figure 4.29 and Figure 4.30.

Table 4.4 Statistic of correct and incorrect cardiovascular disease classification

Signal Type	Class	Correct Classified (%)	Misclassified (%)
Normal	1	97.7	2.3
Bradycardia Arrhythmia	2	95.2	4.8
Tachycardia Arrhythmia	3	100	0
AF	4	97.6	2.4
Total		97.7	2.3

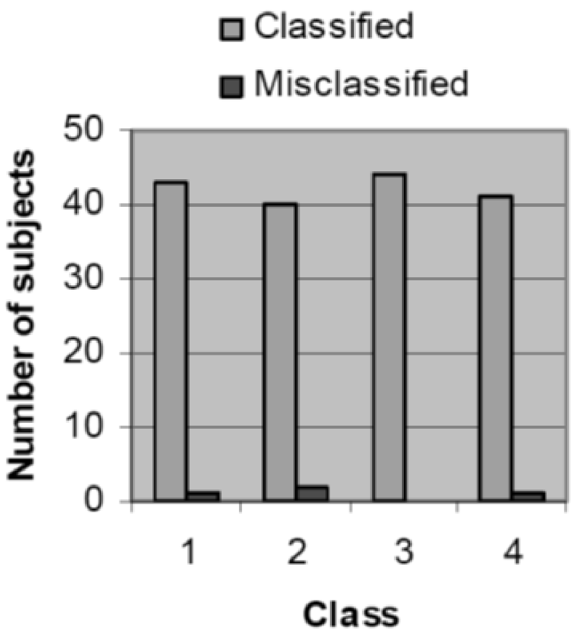


Figure 4.29 Statistic of cardiovascular disease classification

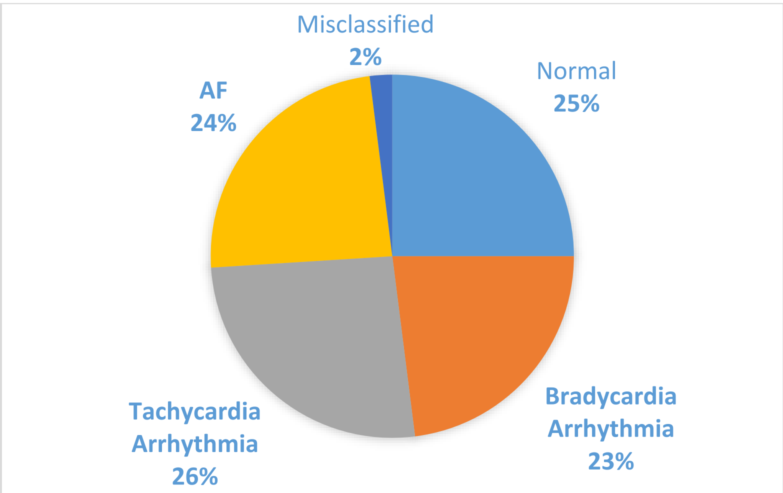


Figure 4.30 Statistic of cardiovascular disease categorization according to class

Table 4.4 and Figure 4.29 reveal the correct classified and misclassified data samples of cardiovascular disease for each class. 97.7% samples from Class 1 were classified correctly and 2.3% data sample is incorrect classified. There are 95.2% samples out of all data samples of Class 2 are classified correctly and 97.6% samples from all data samples from Class 4 were correctly classified. For Class 3, all of their 100% data samples were classified correctly. The AFINN misclassified 4 samples out of all data samples. The statistic of cardiovascular disease categorization according to class also reveals in percentage as displayed in Figure 4.30.

Figure 4.30 reveals the percentage for each data that classified correctly and percentage of misclassified data from the testing data. 25% from the testing data is classified as Normal signals, 23% as Bradycardia Arrhythmia signals, 26% of the data was classified as Tachycardia Arrhythmia signals and the data classified as AFib signals is 24% from the testing data. There is only 2% from the testing data is misclassified by the AFINN system. The confusion matrix in Table 4.5 below showing the categorization results of the AFINN model used for categorization of the EKG signals. This matrix can tell the frequency with which an EKG signals is misclassified as another. The confusion matrix is defined by desired categorization on the rows and actual network outputs on the columns.

According to the confusion matrix,

1 Normal signal from Class 1 was classified incorrectly by the AFINN model as Tachycardia Arrhythmia signal from Class 3.

2 Bradycardia Arrhythmia signals from Class 2 were classified as AFib signals from Class 4 and 1 AFib signal from Class 4 was incorrectly classified as Bradycardia Arrhythmia signal from Class 2.

All of Tachycardia Arrhythmia signals from Class 3 were classified correctly.

Table 4.5 AFINN training performance

Confusion matrix				
Desired output	**Class 1**	**Class 2**	**Class 3**	**Class 4**
Class 1	43	0	0	0
Class 2	0	40	0	1
Class 3	1	0	44	0
Class 4	0	2	0	41

Performance Analysis Result

The categorization performance of the proposed AFINN model was determined by the computation of statistical parameters for instance, sensitivity, specificity and accuracy as follows. Table 4.6 reveals the categorization accuracy determined by AFINN model. The total categorization accuracy determined by AFINN model was 97.68%. The categorization specificity value of Normal, Bradycardia Arrhythmia, Tachycardia Arrhythmia and AFib signals proposed by AFINN system are 100%, 99.23%, 99.22% and 98.46%, respectively. As seen from the Table 4.6, the AFINN classified Normal, Bradycardia Arrhythmia, Tachycardia Arrhythmia and AFib signals with the categorization sensitivity of 97.73%, 95.24%, 100% and 97.62%, respectively.

Table 4.6 AFINN categorization Performance

Datasets	Sensitivity (%)	Specificity (%)	Total accuracy (%)
Normal	98.27	100	98.41
Bradycardia Arrhythmia	95.68	97.87	
Tachycardia Arrhythmia	100	98.14	
AF	98.48	98.36	

From the study, the AFINN algorithm showed significant results of the accuracy of the categorization which are above 90%.The accuracy rates presented are highly encouraging and suggest that Adaptive Fuzzy Inference Neural Network approach is feasible in cardiovascular disease detection. That means, the AFINN categorization system is an excellent system for predicting and classifying. It is able to classify the extracted data from the DWT coefficient of patients EKG signals efficiently and the AFINN model can improve the categorization quality for any EKG signal analysis application. Thus, it can help in improving the life of cardiovascular disease patient.

Chapter 5
Conclusions, Discussion and Suggestions

Conclusions

The primary interest of this study that is the categorization of Normal, Bradycardia Arrhythmia, Tachycardia Arrhythmia and AFib cardiovascular diseases utilizing DWT and AFINN as a Fuzzy Neural Network classifier have been successfully investigated, and the results have been discussed in details in this chapter. Several parameters have been investigated in the study that are the values of energy, maximum, minimum, mean and standard deviation of level 4 DWT detail coefficients. The results indicate that by utilizing DWT and AFINN, the categorization of Normal, Bradycardia Arrhythmia, Tachycardia Arrhythmia and AFib signals can be classified; therefore the primary objective of this study is achieved. The simulation results reveal that the class of cardiovascular disease is well predicted utilizing DWT and AFINN system and the system working well since it achieve the 97.68% of categorization accuracy rate. This result indicates that it has some potential and had been found to be successful in cardiovascular disease detection.

This work is an endeavor to suggest a solution utilizing the hybrids procedures and to determine an optimum EKG categorization scheme designed for the medical environment, where technological advancements have seen changes to many aspects of the daily lives, but there is still a significant gap between the existing solutions and the needs in the medical field. This system provides an analysis system that capable to identify the certain cardiovascular disease.

This analysis system is composed of three major components. Based on the preprocessing stage, it is responsible for gathering the database for patient from MITBIH Arrhythmia database, Intracardiac Atrial Fibrillation Database. This stage have 108 been done by divided each element of the cardiovascular disease phase into Normal signal, Tachycardia Arrhythmia signal, Bradycardia Arrhythmia signal and AFib signal. The signals are successfully can be evaluated and processed. The data gathered from the selected databases are connected to numerical analysis software where the data are processed. The second part of the analysis system is based on wavelet analysis theories. This takes Discrete Wavelet Transform as a medium to process the patient data. Feature extraction techniques are applied to the patient data and the characteristic points of interests are being extracted which are Energy, Maximum, Minimum, Mean and Standard Deviation values. These data provide meaningful data for the diagnosis of likely cardiovascular diseases. The data are successfully can be extracted from 172 subjects of patients signal in classifying the Normal signal, Tachycardia Arrhythmia signal, Bradycardia Arrhythmia signal and AFib signal. Finally, the last part of this system involve the Fuzzy Neural Network classifier which is Adaptive Fuzzy Inference Neural Network(AFINN) in classifying the cardiovascular disease where the decision of cardiovascular disease is made based on the extracted features processed by Discrete Wavelet Transform. AFINN plays a considerable role in dealing with uncertainty when making decisions in medical application. The ability to learn how to determine results from the sample data is its biggest asset. In AFINN, the membership function parameters are extracted from dataset that describes the behavior of the EKG signals. AFINN was used to detect EKG changes while the wavelet coefficients are defined as its inputs. The AFINN presented in this study was trained with the back propagation gradient descent method in combination with the least squares method. AFINN classifier is able to get total categorization accuracy rate up to 97.68%, sensitivity rate are 97.73%, 95.24%, 100% and 97.62%, for Normal, Bradycardia Arrhythmia, Tachycardia Arrhythmia and AFib class. Then, the specificity rate that achieved in classifying the Normal, Bradycardia Arrhythmia, Tachycardia Arrhythmia and AFib class are 100%, 99.23%, 99.22% and 98.46%, respectively. The AFINN model presented in this study prove that it achieved the higher rates of categorization accuracy.

Discussion

There are many types of cardiovascular disease which their EKG signals vary closely in amplitude and time duration and represent the expected disease. So the signals must be understood and recognize clearly to make sure the signals are not misclassified. The increased of input nodes used in AFINN model will cause increasing of the number of rules, so that it will affect to increase the time to run the sample data used in the training process of the AFINN system. The increasing of input nodes also will cause the networks to learn more complex functions and relatively increase the number of training epochs to complete the learning process until the root mean square error close into zero error rates.

Due to large number of patients in intensive care units and the need for continuous observation, the current technology development can help to develop the automated EKG monitoring system that allows the system for continuous heart signal monitoring capabilities. By automating the EKG monitoring process, the most updated data for all patients are made available at all times and avoided the delays treatments. It is also can intended to give support to the current health care environments. The characteristics of the wave features for the EKG analysis can be extended to the other form by utilizing a better or other hybrid procedures to evaluate the selected features which suitable for many types of cardiovascular disease detection.

The quality of accuracy, sensitivity and specificity of EKG analysis can be improved by adding more input databases in the training samples , so that the system are able to learn more and train the system to identify the signal accurately. The distinguishing accuracy of AFINN model which combined the neural network adaptive capabilities and the fuzzy logic qualitative approach also can be improve by combining several AFINN classifier in input data training stage. The performance of accuracy and training time for classifying the cardiovascular disease of EKG analysis systems that widely done in numerical analysis software can be improved by embeds the system in the Field Programmable Logic Arithmetic (FPGA). In the code development, more accurate procedures rates should be used.

Suggestions

Automatic cardiac abnormality categorization is necessary for real time application. The categorization accuracy can improve by extracting the better features of EKG signal. Future developments can be made as follows

· To design better feature extraction methodology which can improve the categorization result of cardiac arrhythmias in EKG signal.

- To analyze the categorization accuracy utilizing dissimilar classifier such that it can classify the beat arrhythmias in the approved manner.
- To modify the network structure according to cost function of multilayer neural network so that it can achieve better categorization accuracy as compared to existing EKG beat classifier.
- Real time operation for recognizing the cardiac arrhythmias can also be done since the methodology uses the automatic detection of R-peaks and feature extraction techniques.

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APPENDICES

APPENDIX A

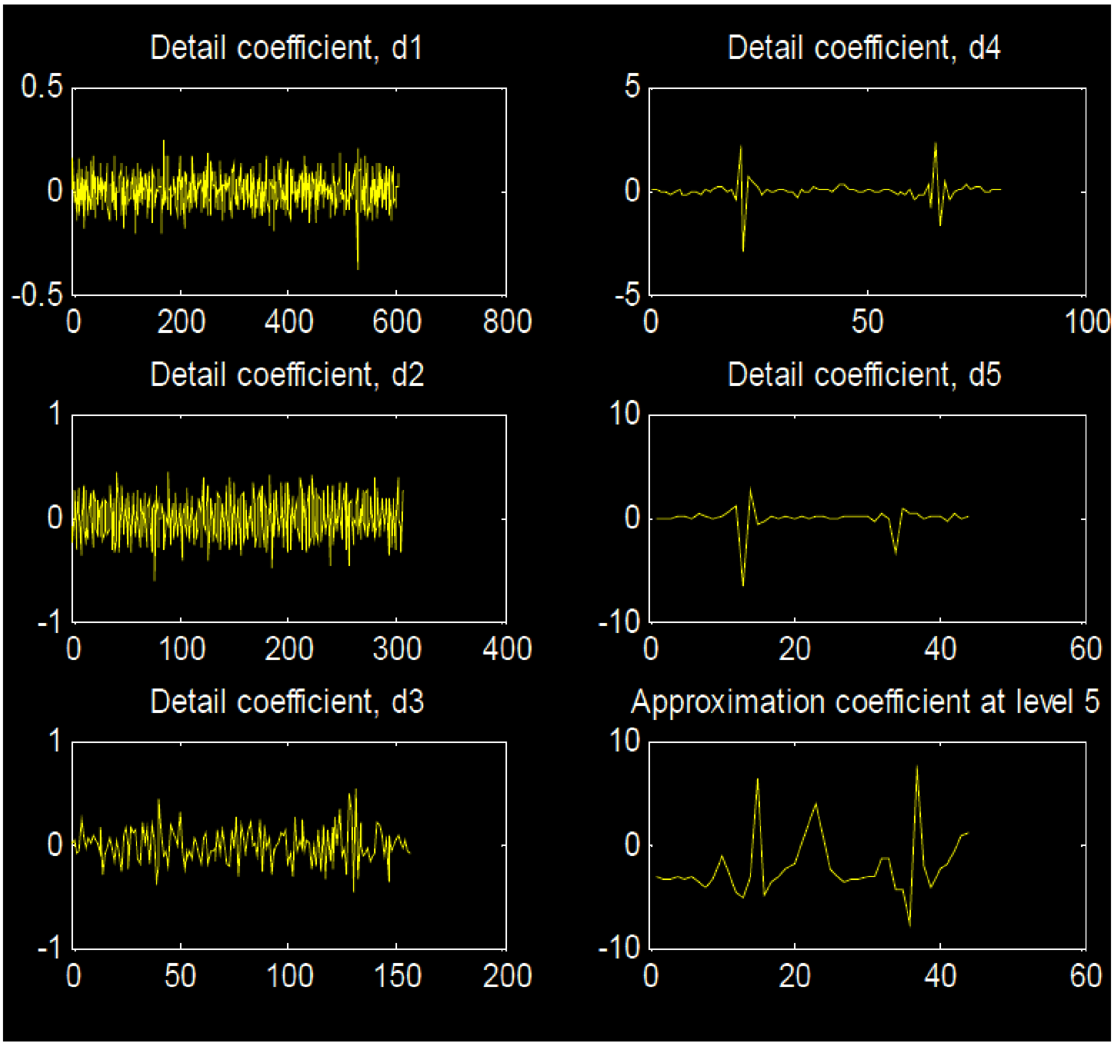
The dataset for the extracted parameter from the DWT coefficient

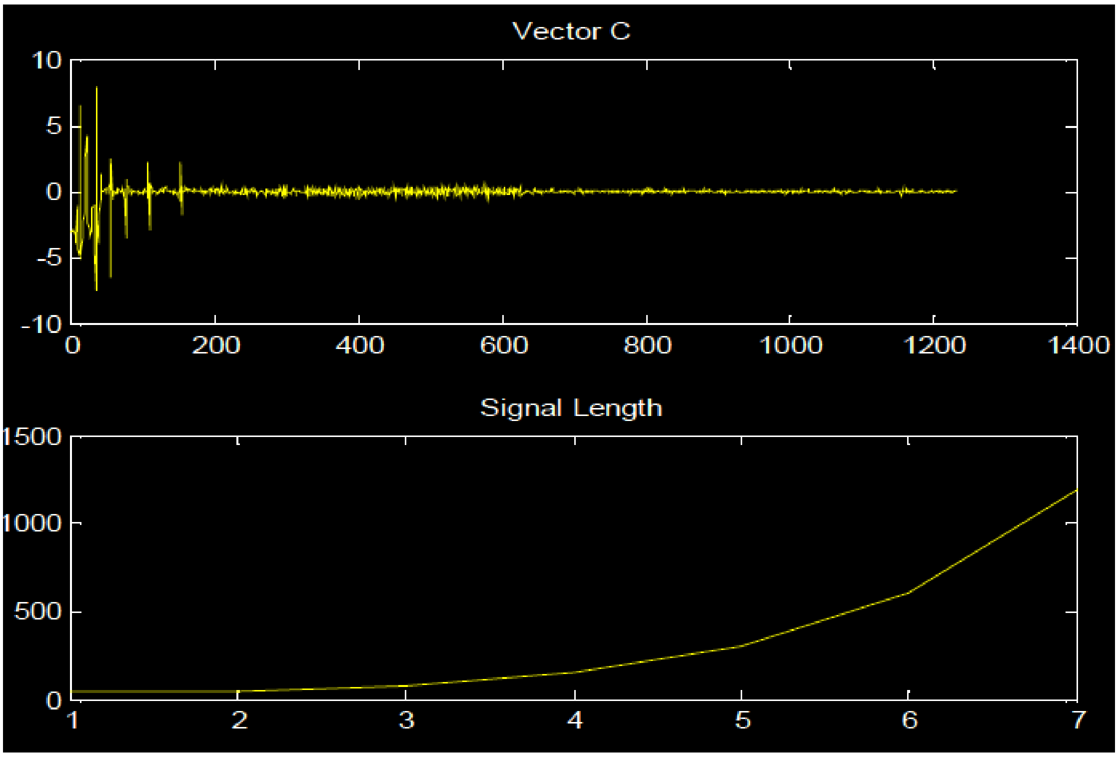
Cardiovascular disease type	Energy	Max	Min	Mean	SD
Normal	2.2307	2.2777	-2.9128	-0.0084	0.5588
	2.3509	2.3143	-2.8845	-0.0089	0.5688
	2.1587	2.2954	-2.8956	-0.0093	0.5736
	2.142	2.2858	-2.9135	-0.0083	0.5825
	2.0987	2.2896	-2.8859	-0.0091	0.5932
	2.1186	2.2457	-2.8268	-0.0088	0.5748
	2.1253	2.2691	-2.8973	-0.0089	0.5578
	2.1403	2.2859	-2.8638	-0.0094	0.5737
	2.1087	2.3748	-2.8594	-0.0079	0.5409
	2.0921	2.2756	-2.9134	-0.0071	0.5525
Bradycardia Arrhythmia	0.0168	0.5263	-1.1436	-0.00459	0.1452
	0.0151	0.5229	-1.1444	-0.00477	0.1481
	0.0153	0.5237	-1.1424	-0.00458	0.1469
	0.0191	0.5232	-1.1435	-0.00464	0.1465
	0.0173	0.5231	-1.1439	-0.00446	0.1476
	0.0171	0.5255	-1.1451	-0.00451	0.1468
	0.0179	0.5251	-1.1435	-0.00457	0.1477
	0.0131	0.5282	-1.1437	-0.00462	0.1479
	0.0177	0.5236	-1.1428	-0.00438	0.1456
	0.0174	0.5275	-1.1432	-0.00421	0.1464
Tachycardia Arrhythmia	6.9132	2.9568	-2.3876	0.0635	0.8888
	6.9459	2.9453	-2.3922	0.0644	0.8234
	6.9752	2.9559	-2.3902	0.0699	0.8541
	7.0114	2.9669	-2.3909	0.0676	0.8693
	6.9383	2.9647	-2.3865	0.0642	0.8647
	7.0421	2.9662	-2.3832	0.0648	0.8639
	6.9567	2.9549	-2.3865	0.0683	0.8104
	7.0243	2.9557	-2.3937	0.0676	0.8462
	7.0179	2.9573	-2.3848	0.0653	0.8397
	6.9687	2.9565	-2.3929	0.0642	0.8542
AF	0.0153	0.677	-0.9324	-0.0197	0.2123
	0.0139	0.654	-0.9678	-0.0163	0.2788
	0.0144	0.687	-0.9894	-0.0164	0.2896
	0.0143	0.643	-0.9947	-0.0124	0.2652
	0.0152	0.711	-0.9536	-0.0131	0.2341
	0.0146	0.669	-0.9561	-0.0118	0.2376
	0.0159	0.712	-0.9756	-0.0186	0.2426
	0.0155	0.686	-0.9646	-0.0163	0.2456
	0.0151	0.694	-0.9564	-0.0132	0.2647
	0.0151	0.728	-0.9684	-0.0136	0.2656

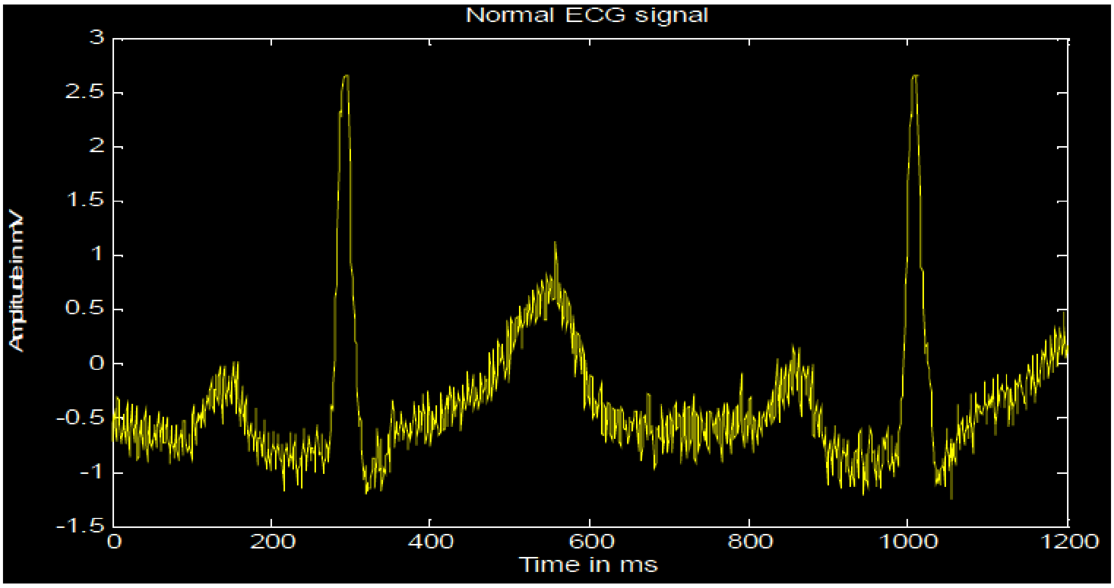
APPENDIX B

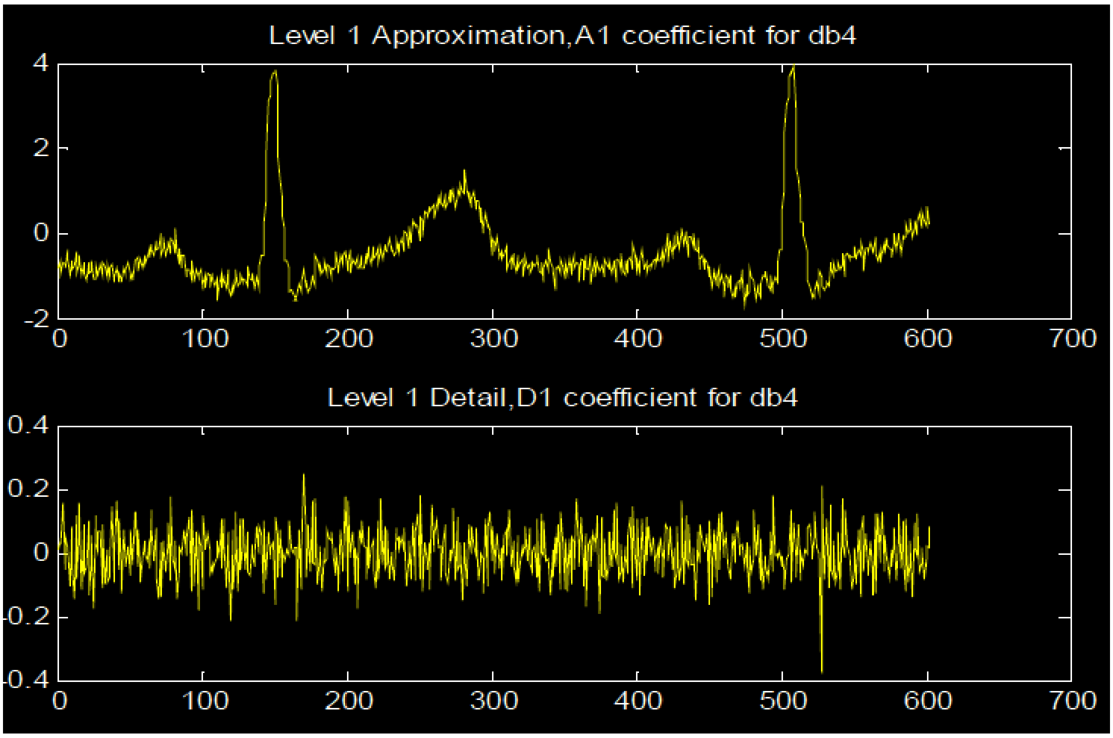
The input data in the preprocessing and DWT stage

Normal Signal

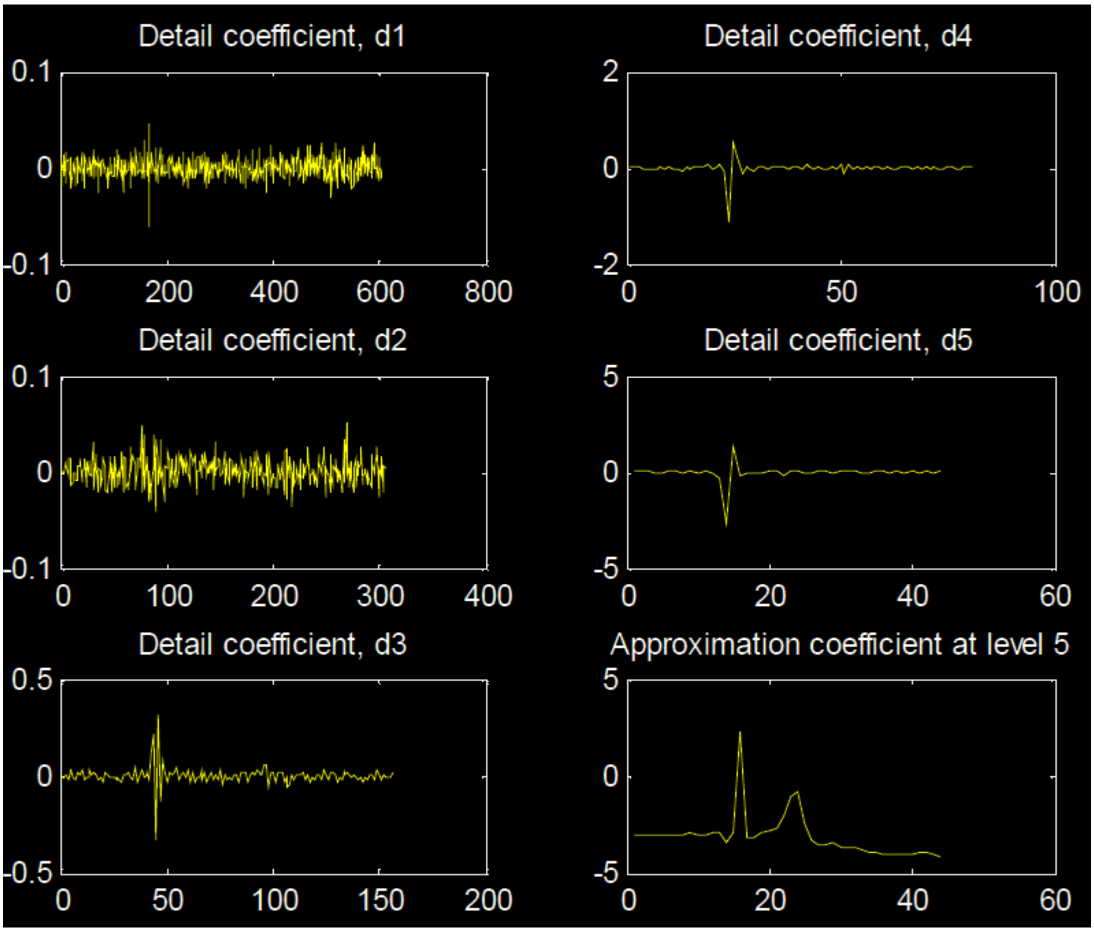


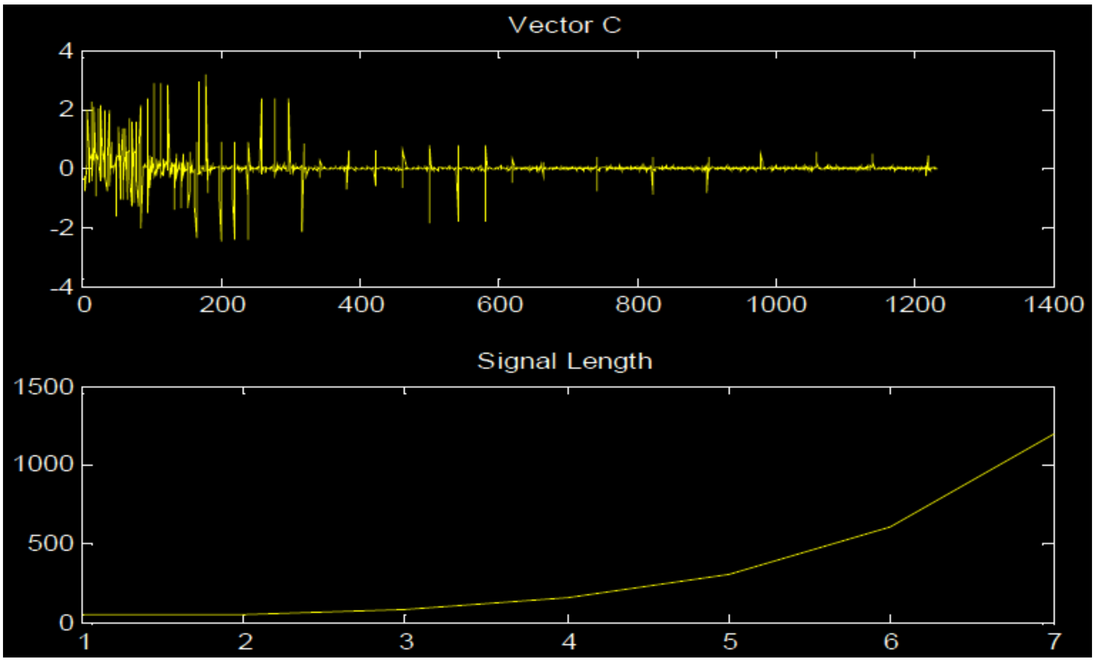

Vector C
10
5
0
-5
-10
0
200
400
600
800
1000
1200
1400
Signal Length
1500
1000
500
0
1
2
3
4
5
6
7

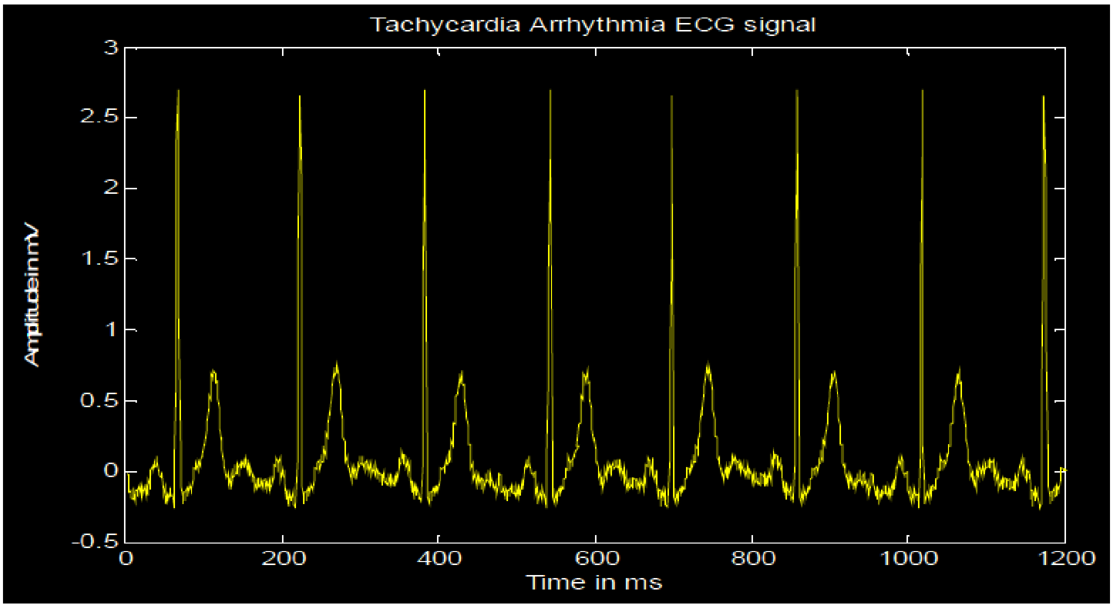

Normal ECG signal
Amplitude in mV
3
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
0
200
400
600
800
1000
1200
Time in ms

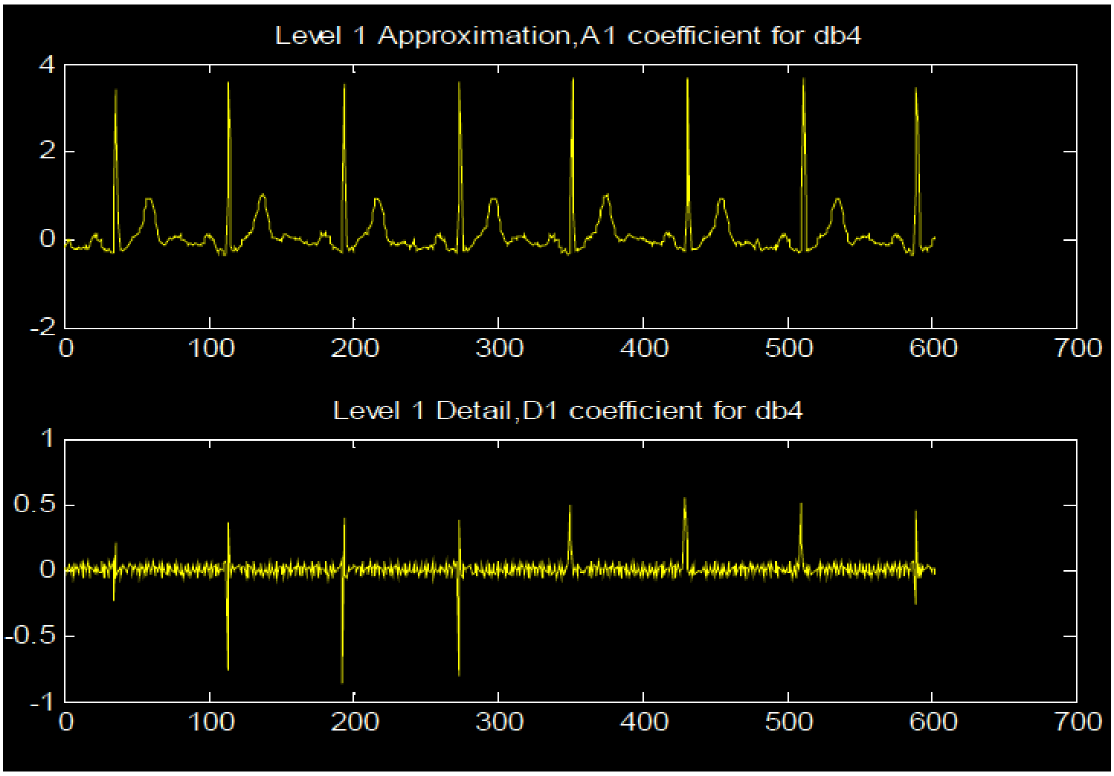

Level 1 Approximation,A1 coefficient for db4
4
2
0
-2
0
100
200
300
400
500
600
700
Level 1 Detail,D1 coefficient for db4
0.4
0.2
0
-0.2
-0.4
0
100
200
300
400
500
600
700

Bradycardia Arrhythmia Signal

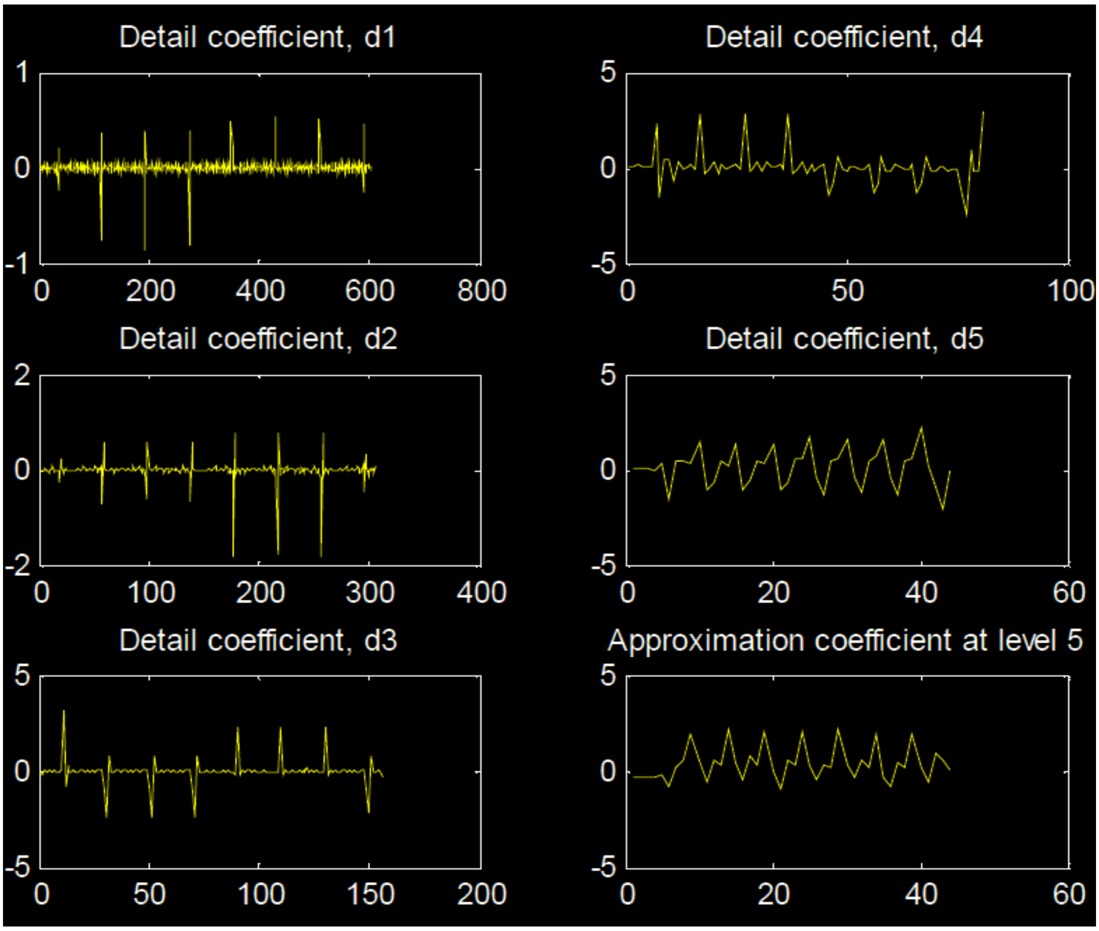


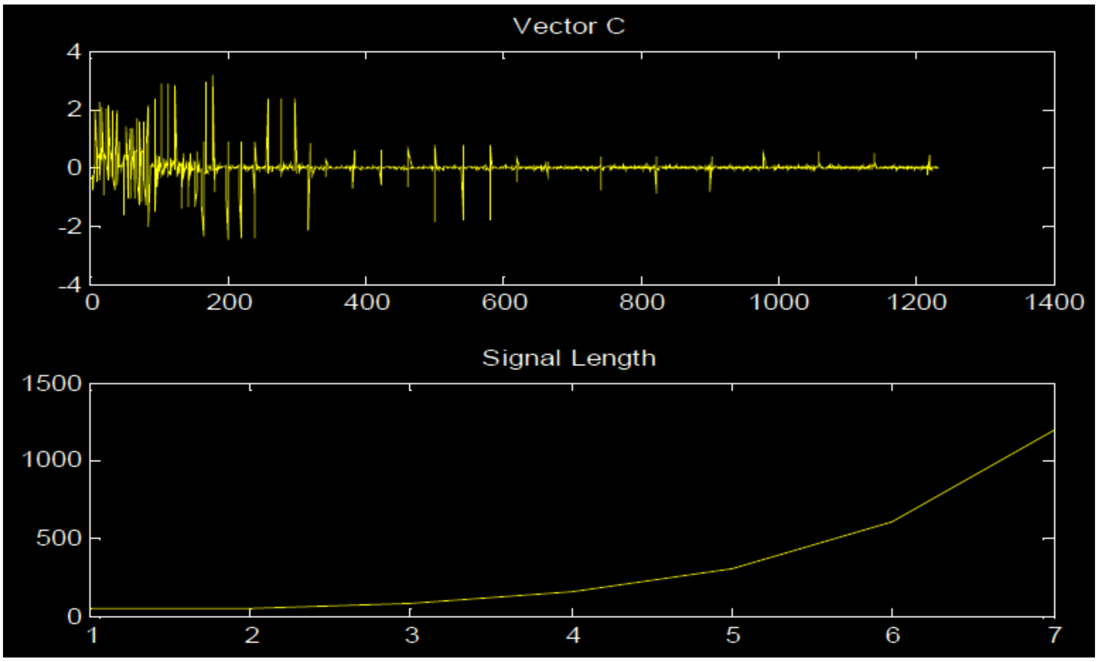


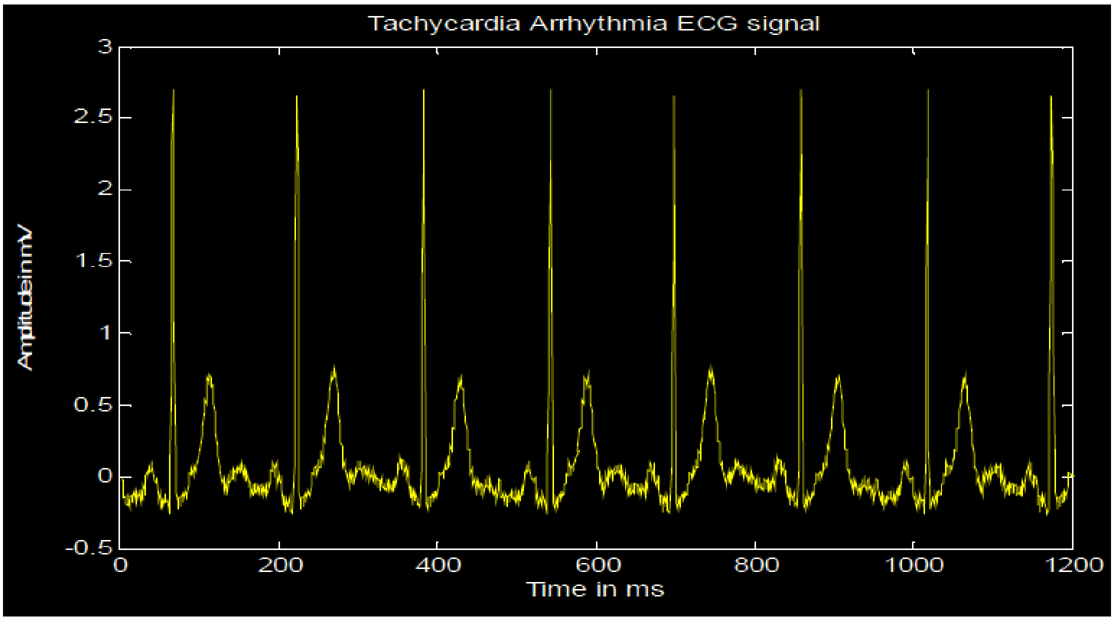

Tachycardia Arrhythmia ECG signal
Amplitude in mV
Time in ms
3
2.5
2
1.5
1
0.5
0
-0.5
0
200
400
600
800
1000
1200

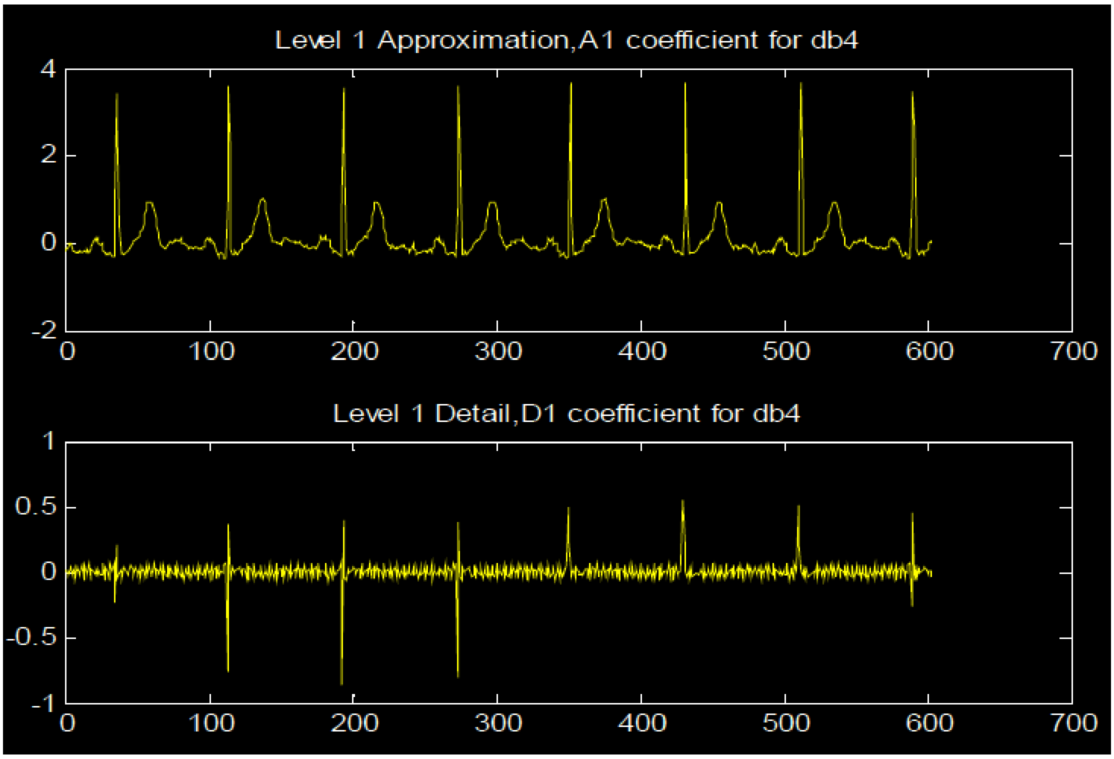

Level 1 Approximation,A1 coefficient for db4
4
2
0
-2
0
100
200
300
400
500
600
700
Level 1 Detail,D1 coefficient for db4
1
0.5
0
-0.5
-1
0
100
200
300
400
500
600
700

Tachycardia Arrhythmia Signal

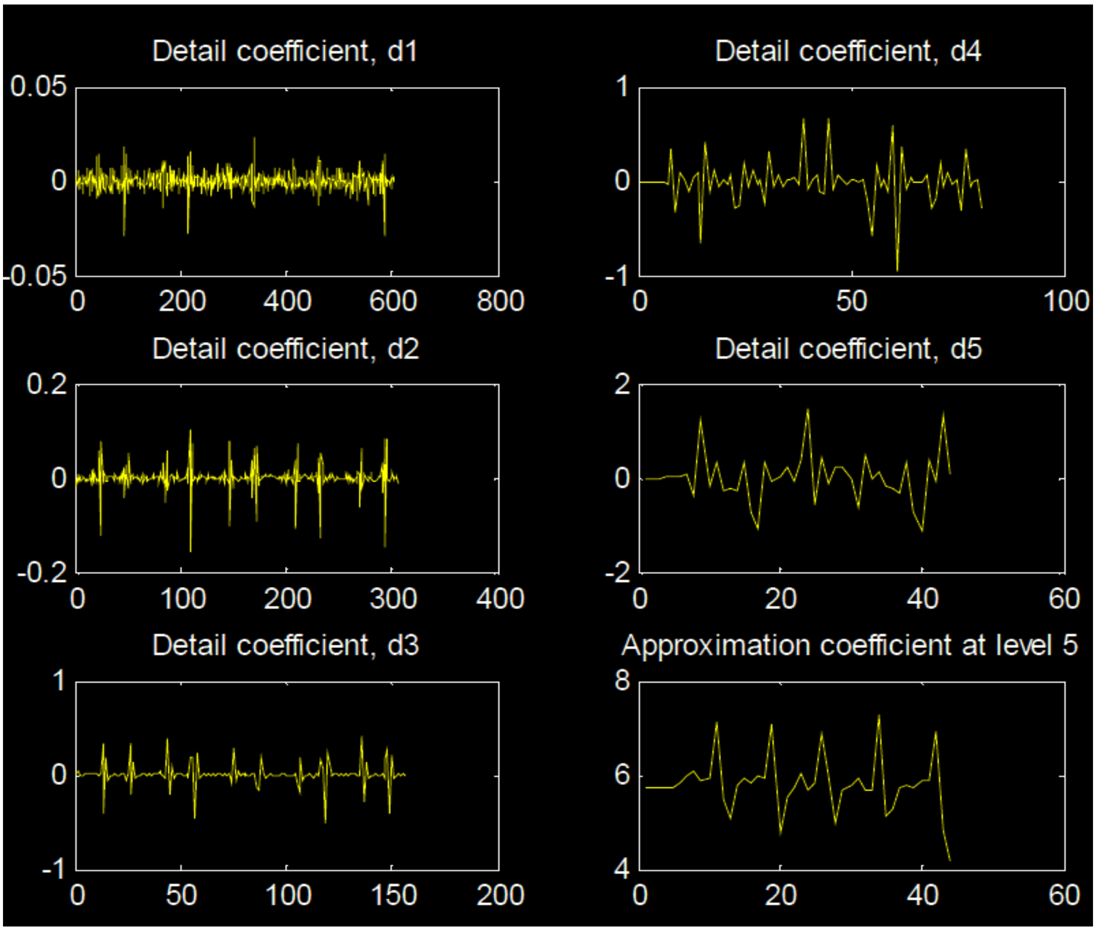


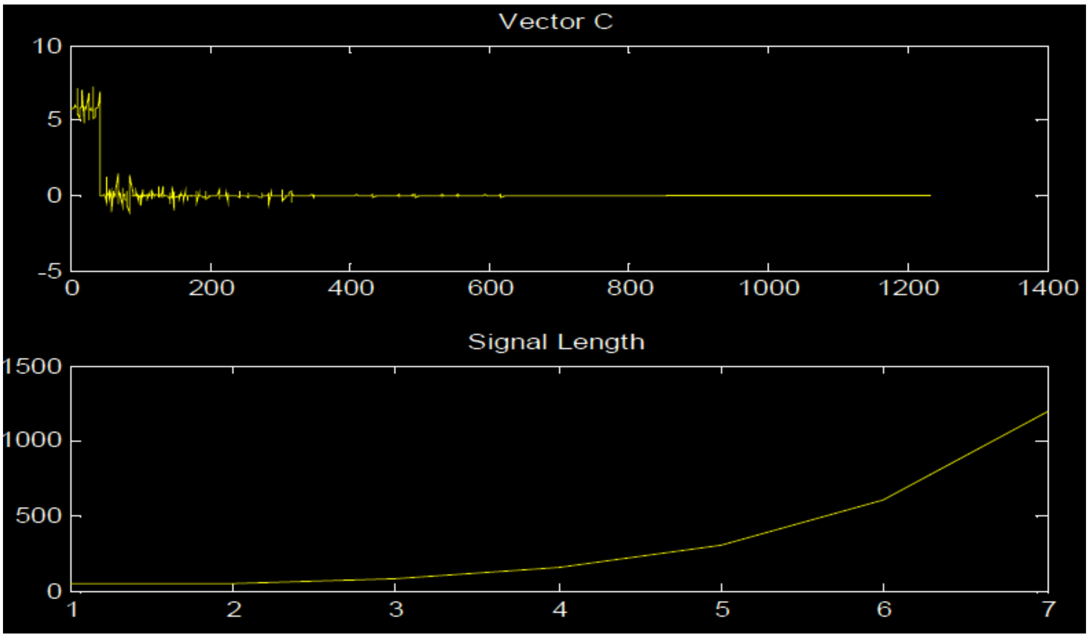


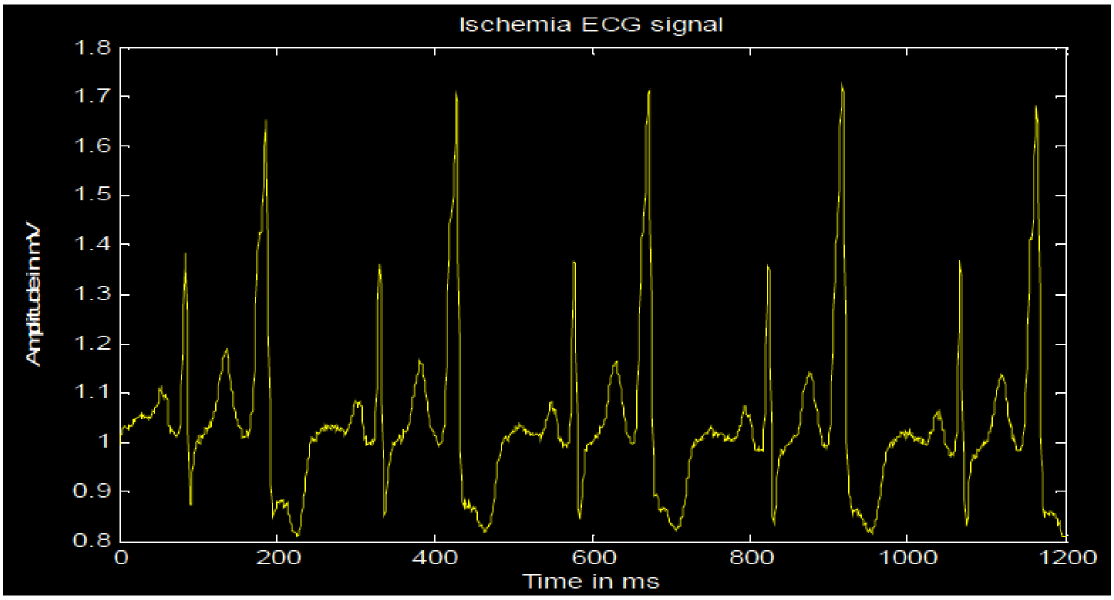

Tachycardia Arrhythmia ECG signal
Amplitude in mV
3
2.5
2
1.5
1
0.5
0
-0.5
0
200
400
600
800
1000
1200
Time in ms

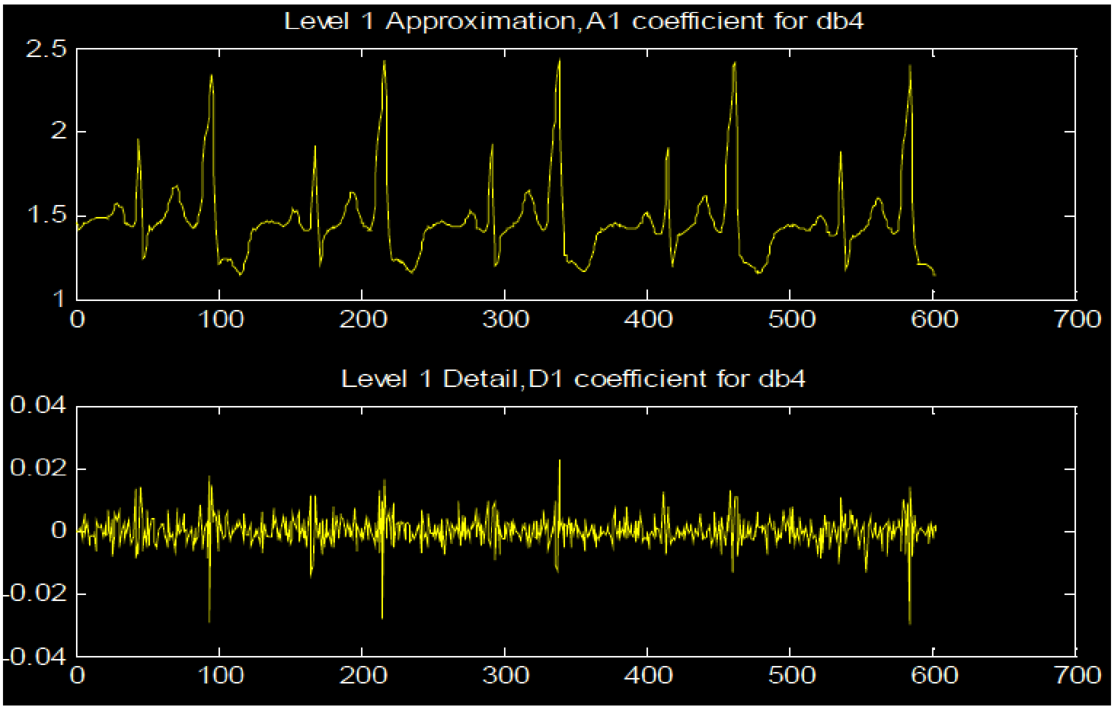

Level 1 Approximation,A1 coefficient for db4
4
2
0
-2
0
100
200
300
400
500
600
700
Level 1 Detail,D1 coefficient for db4
1
0.5
0
-0.5
-1
0
100
200
300
400
500
600
700

AFIB Signal


Detail coefficient, d1
0.05
0
-0.05
0 200 400 600 800
Detail coefficient, d4
1
0
-1
0 50 100
Detail coefficient, d2
0.2
0
-0.2
0 100 200 300 400
Detail coefficient, d5
2
0
-2
0 20 40 60
Detail coefficient, d3
1
0
-1
0 50 100 150 200
Approximation coefficient at level 5
8
6
4
0 20 40 60


Vector C
10
5
0
-5
0 200 400 600 800 1000 1200 1400
Signal Length
1500
1000
500
0
1 2 3 4 5 6 7


Ischemia ECG signal
Amplitude in mV
Time in ms
1.8
1.7
1.6
1.5
1.4
1.3
1.2
1.1
1
0.9
0.8
0
200
400
600
800
1000
1200


Level 1 Approximation, A1 coefficient for db4
2.5
2
1.5
1
0
100
200
300
400
500
600
700
Level 1 Detail, D1 coefficient for db4
0.04
0.02
0
-0.02
-0.04
0
100
200
300
400
500
600
700

Biography

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