Sudan University of Science and Technology

College of Graduate Studies

Department of Biomedical Engineering

DESIGN FOR REAL TIME HEART SOUNDS RECOGNITION SYSTEM

تصميم نظام التعرف على أصوات القلب في الزمن الحقيقي

Submitted in partial fulfillment of the requirement of M.Sc (Honor) Degree in Biomedical Engineering

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بسم الله الرحمن الرحيم

الآيــة

ٱلَّذِينَ ءَامَنُواْ وَتَطۡمَئِنُّ قُلُوبُهُم بِذِكۡرِ ٱللَّهِۗ أَلَا بِذِكۡرِ ٱللَّهِ تَطۡمَئِنُّ
ٱلۡقُلُوبُ ﴿٢٨﴾

صدق الله العظيـم

سورة الرعد (الآية 28)

Dedication

To …

MY LOVELY BELOVED father

To …

MY sweetest beloved mother

I dedicate this RESEARCH

‘‘‘‘

Acknowledgement

All thanks to Allah Almighty who gave me the strength, Determination, health and granted me with patience to successfully complete of this research.

I cannot express enough thanks to my supervisor **Dr. Magdi Baker M.Ameen** for his continued guidance, support, unlimited helps and encouragement; I offer my sincere appreciation for the learning opportunities provided by you.

My completion of this research could not have been accomplished without the support of my parents, family and friends. My deepest gratitude, and special appreciation and thanks to: Biomedical Engineering department staff, Sudan Heart Center, Best-Care Hospital, Eng. Ayman Kenana, and Eng. Ola Salahaddin for their support and guidance. Your encouragement when the times got rough are much appreciated and duly noted.

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List of Abbreviations

AP: Atrial Pressure. ....

CAD: Coronary Artery Disease. ....

CCS: Code Composer Studio...

CPU: Centeral Processing Unit...

db: Debauches. ....

DFT: Disceret Fourier Transform...

DSP: Digital Signal Processing ....

DWT: Disceret Wavelet Transform..

ECG: Electrocardiogram...

ERT: Embedded Rearl Time..

FFT: Fast Fourier Transform ....

FIR: Finite Impulse Response..

FN: False Negative ....

FP: False Positive...

FT: Fourier Transform. ....

HSs: Heart Sounds ....

IDE: Integrated Development Environment. ....

IDWT: Inverse Disceret Wavelet Transform...

IIR: Infinite Impulse Response ....

I/O: Input/Output ....

ISRs: Interrupt Service Routines. ....

JFET: Junction Field Effect Transistor ....

LED: Light Emitting Diode ....

LMS: Least Mean Squre

LPF: Low Pass Filter

LSs: Lung Sounds

MRA: Multi Resolution Analysis

OS: Operating System

PC: Personal Computer

PCG: Phonocardiogram

PSD: Power Spectrum Density.

PWVD: Pseudo Winger Ville Distribution.

RLS: Recursive Least Squre

RTW: Real Time Workshop

S_1: First Heart Sound

S_2: Second Heart Sound

S_3: Third Heart Sound

S_4: Fourth Heart Sound

STFT: Short Time Fourier Transform.

TI: Texas Instrument.

TLC: Target Language Configuration.

TN: True Negative.

TP: True Positive.

VP: Ventricular Pressure

ABSTRACT
Auscultation is a technique, in which Physicians used the stethoscope to listen to patient's heart sounds in order to make a diagnosis. However, the determination of heart conditions by heart auscultation is a difficult task and it requires special training of medical staff. On the other hand, in primary or home health care, when deciding who requires special care, auscultation plays a very important role; and for these situations, an ''intelligent stethoscope'' with decision support abilities is highly needed and it would be a great added value.

In this study a reliable Real Time Heart sounds recognition system has been, introduced, designed, implemented and successfully tested.

The system algorithm has been realized in two phases, offline data phase and real data phase. For offline data phase, 30 cases of Heart Sounds (HSs) files were collected from medical students and doctor's world website, and then the background noise is minimized using wavelet transform. After that, graphical and statistics features vector elements are formed for both time and frequency domain. Finally, classification process was accomplished using look-up table. The implementation of the proposed algorithm produced accuracy of 90%, and sensitivity of 87.5%.

In experimental phase (real time data), electronic stethoscope has been designed and recorded HSs directly from 30 volunteers with 17 normal case and 13 various pathologies cases. In preprocessing stage, an adaptive filter was used to filter heart sounds from lung sounds, due to lung sound overlapped with heart sound in sub frequency band. Then, wavelet was applied to minimized background noise and features are formed for classification process, as well as offline data phase. The implementation of the proposed algorithm produced accuracy of 80%, and sensitivity of 82.4%.

The advanced steps for implementing a portable module by embedded DSP have been successfully achieved. Firstly, System SIMULINK model was built, and then real time workshop was used to generate embedded coder, finally the code files linked to Code Composer Studio Software and running the project successfully.

المستخلص

الفحص بالسماعة الطبية هو أسلوب يستخدمه الأطباء للإستماع إلى أصوات قلب المريض، ولكن تحديد الحالة الصحية لقلب المريض عن طريق الفحص بالسماعة الطبية هي مهمة صعبة وتتطلب تدريبا خاصا للطاقم الطبي. لذا في مجال الرعاية الصحية الأولية والمنزلية عندما يحتاج المريض رعاية صحية خاصة فإن تصميم سماعة ذكية ستكون ذات قيمة فعاله لدعم القرار.

في هذا البحث تم تقديم وتصميم وتنفيذ نظام موثوق في الزمن الحقيقي لتمييز أصوات القلب كما تم إختبار هذا النظام بنجاح.

خوارزمية البحث تم تنفيذها على مرحلتين، مرحلة جمع البيانات من الشبكة العنكبوتية محفوظة كقاعدة بيانات ومرحلة جمع البيانات في الزمن الحقيقي.

في مرحلة قاعدة بيانات الشبكة العنكبوتية تم جمع 30 ملف لأصوات القلب وبحالات مختلفة من مواقع لطلاب الطب والأطباء، وفي مرحلة المعالجة الأولية للإشارات، تمت تنقية أصوات القلب من إشارات الضجيج بإستخدام المويجات، ثم إستخلصت وشكلت الخصائص الإحصائية والأشكال المميزه للإشارة في المجالين الزمني والترددي وذلك في مرحلة تشكيل خصائص الإشارة. أخيرا قورنت خصائص الإشارات التي يراد تصنيفها مع خصائص الإشارة المرجعية بإستخدام جدول مطابقة الخصائص وذلك بغرض التصنيف، حيث أبرزت الخوارزمية دقة بنسبة 90% وحساسية بنسبة 87.5%.

في مرحلة جمع البيانات في الزمن الحقيقي، تم تصميم سماعة طبية إلكترونية لتسجيل الإشارات في الزمن الحقيقي من 30 متطوع، 17 منهم بحالة طبيعية و13 بحالات مختلفة لأمراض القلب. في مرحلة المعالجة الأولية تم فصل أصوات القلب من أصوات الرئة نتيجة لتداخلهما في نطاق بعض الترددات، وطبقت المويجات لتقليل الضجيج الناتج من بيئة التسجيل وسريان الدم وانقباض العضلات. ومن ثم شكلت الخصائص المميزة للإشارة وذلك لتطبيقها في مرحلة التصنيف، بنفس طريقة قاعدة بيانات الشبكة العنكبوتية سالفة الذكر، حيث أبرزت الخوارزمية دقة بنسبة 80% وحساسية بنسبة 82.4%.

تم تنفيذ خطوات التصميم المتقدمة لتقديم نموذج محمول بإستخدام عتاد معالج الإشارات الرقمية، حيث تم بناء نظام المحاكاه (السيمولنك) ومن ثم تم إستخدام حقل الوقت الحقيقي لتوليد ملفات بلغة السي وذلك لنسخ وربط هذه الملفات ببرنامج التطويرالبيئي المتكامل حيث تم بناء وتشغيل المشروع بنجاح.

CHAPTER ONE

INTRODUCTION

1.1 General Overview:

Auscultation is a technique, in which Physicians used the stethoscope to listen to patient's heart sounds in order to make a diagnosis [1, 2]. Physicians are particularly interested in abnormal sounds, which may suggest the presence of a cardiac pathology and also provide diagnostic information [3, 4].

Nowadays, modern technology has provided more powerful tools to evaluate the information related to heart sounds that traditional tools like stethoscope cannot achieve [5]. One of the most common methods used for listening and tracking the heart sounds is to record them with special devices, the recorded heart sounds is known as PCG (phonocardiogram) signal. It is a particularly useful diagnosis tool since it contains different timings and relative intensities of heart beat sounds which are directly related to heart activity [6]. The development of new digital signal processing techniques, such as a pattern recognition and time frequency analysis and representation has improved the HSs signal analysis and therefore make it actually as a non-invasive technique in aid to heart activity diagnosis [7].

1.2 Significance of the study

Cardiac murmurs are often the first sign of pathological changes in the heart valves. Doppler-echocardiography and magnetic resonance imaging are today well established tools in the diagnosis of heart valve disorders, while the classic techniques of auscultation and phonocardiography are playing a diminishing role in modern specialist care. However, in primary or home health care, when deciding who requires special care, auscultation still plays a very important role. For these situations, an ‘‘intelligent stethoscope’’ with decision support abilities would be a great value.

1.3 Problem Statements

Determination of heart conditions by heart auscultation is a difficult task and it requires special training of medical staff. The heart sound is usually detected by human ear using acoustical stethoscope, which is inefficient due to the limitations of the human's ear sensitively, especially that heart sounds are very week in intensity and low in frequencies.

1.4 Objectives

The objectives of this research are general objective and specific objectives.

1.4.1 General Objective

The main purpose of this research is to design a real time heart sounds recognition system, which supports healthcare physicians in decision making.

1.4.2 Specific Objectives are to:

1. Design and implement a reliable electronic stethoscope.
2. Record heart sounds directly from patients, by using the designed electronic stethoscope, then transmitted it to PC to be analyzed and processed.
3. Simulate the hardware design flow for Embedded DSP using Code Composer Studio software.
4. Classify heart sounds into normal and abnormal cases.

1.5 Methodology

The system algorithm has been realized in two phases, offline and real time phase. For offline data phase, 30 cases of HSs files were collected from medical students and doctor's world website, and then MATLAB software was used to analyze and process the collected signals based on digital signal processing (DSP).

For experimental phase (real time data), A designed of an electronic stethoscope was used to record signals directly from patients, then transmit the recorded signals to PC to be analyzed and processed.

The decision-making process comprises of three main stages:

At the first stage, an adaptive filter was applied in real time data to filter lung sounds from heart sounds. This process is not needed when using offline data, since it consist of pure heat sounds only. Both data (offline and online data) were processed using wavelet transform, to reduce the background noise. At the second stage, graphical and statistics features vector elements are formed for both time and frequency domain. At the final stage, classification process was accomplished by look-up table.

1.6 Thesis layout:

This research consists of five chapters:

Chapter one is an introduction, Chapter two deals of theoretical background and discusses the related literature reviews. The design and implementation of a Real time heart sounds recognition system was explained in chapter three. The results and discussion were illustrated in chapter four, finally conclusions and recommendations presented in chapter five.

CHAPTER TWO

THEORETICAL BACKGROUND AND REVIEWS

2.1 The human heart

The heart is located in chest between the lungs behind the sternum and above the diaphragm. It is surrounded by the pericardium. Its size is about that of a fist, and its weight is about 250-300g. Its center is located about 1.5 cm to the left of the midsagital plane. An overall view is given in figure (2.1). [9]

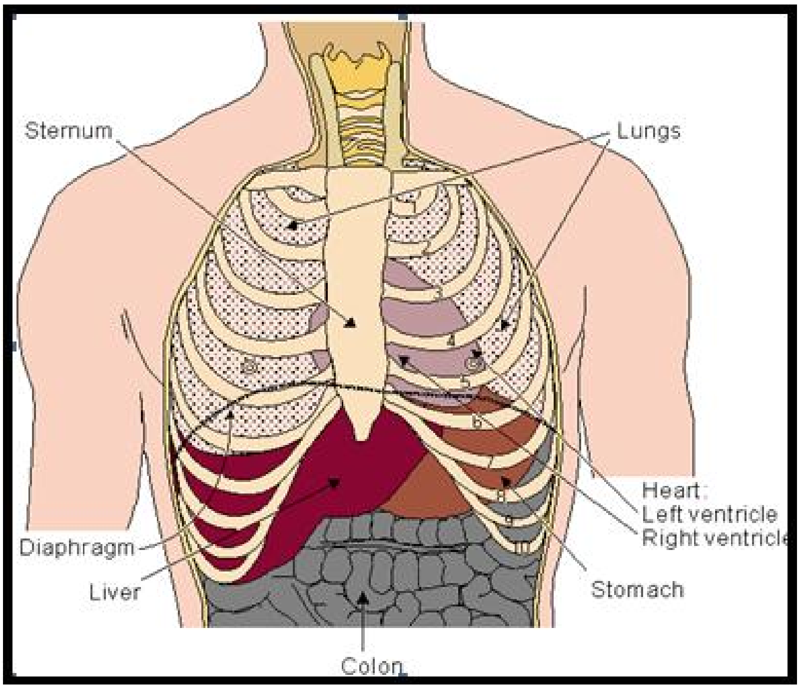


Figure (2.1): Location of the heart in the thorax. [9]

2.1.2 Anatomy of the heart

The walls of the heart are composed of cardiac muscle, called myocardium. It also has striations similar to skeletal muscle. It consists of four compartments: the right and left atria and ventricles. The heart is oriented so that the anterior aspect is the right ventricle while the posterior aspect shows the left atrium figure (2.2). The left atria form one unit and the ventricles another. The left ventricular free wall and the septum are much thicker than the right ventricular wall.

The heart has four valves. Between the right atrium and ventricle lies the tricuspid valve. The mitral valve lies between the left atrium and ventricle. The pulmonary valve lies between the right ventricle and the pulmonary artery, while the aortic valve lies in outflow tract of the left ventricle (controlling the aorta).

The blood returns from the systemic circulation to the atrium and from there goes through the tricuspid valve to the right ventricle. It is ejected from the right ventricle through the pulmonary valve to the lungs.

Oxygenated blood returns from the lungs to the left atrium and from there through the aortic valve to aorta the systemic circulation.

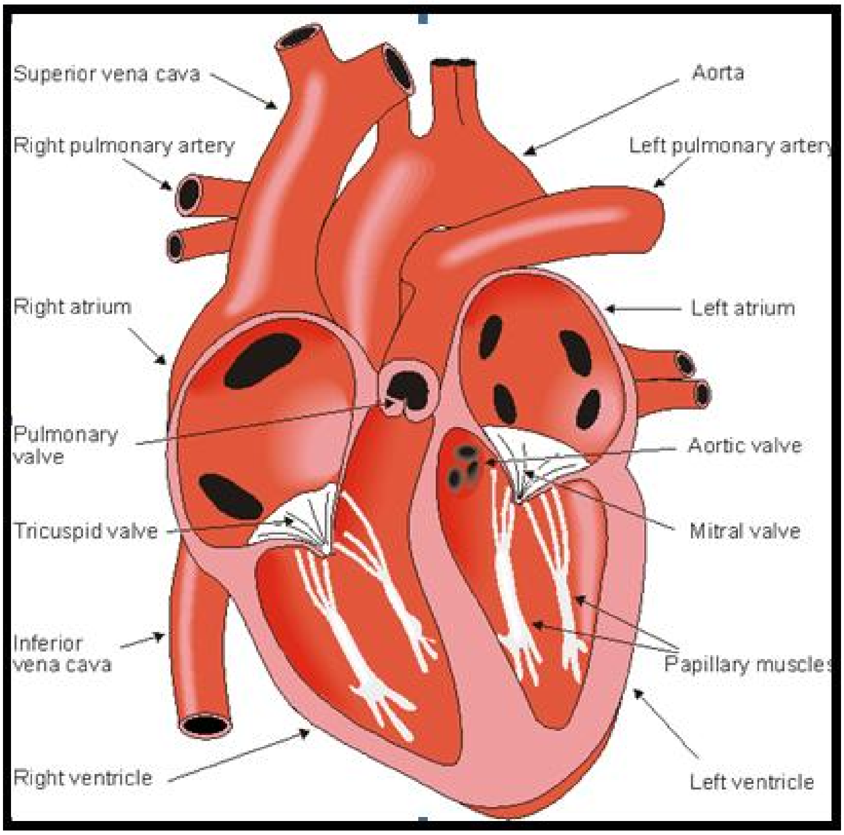


Figure (2.2): The Anatomy of the Heart and Associated Valves. [9]

2.1.3 Cardiac Cycle

The cardiac cycle is a synchronized sequence of contractions and relaxations of the atria and ventricles during which major events occur, such as valves opening and closing and changes in blood flow and pressure. Each contraction and relaxation is referred to as systole and diastole, respectively. Figure (2.3) shows the events related to the cardiac cycle [10].

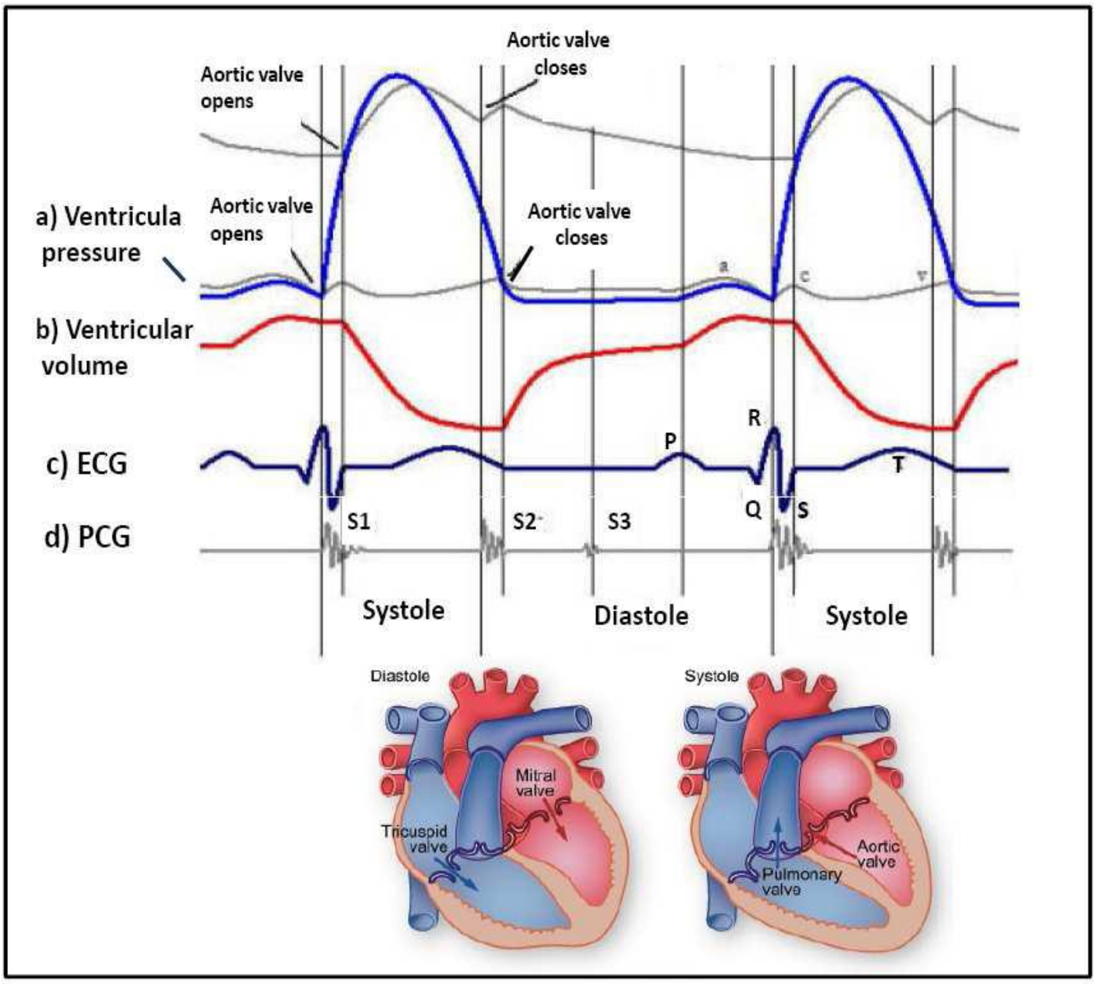


Figure (2.3): Signals Of Cardiac Cycle (A) Ventricular Pressure, (B) Ventricular Volume, (C) ECG And (D) PCG (Heart Sounds). [10]

The diagram starts at late ventricular diastole. At this stage, the AV valves are open and the ventricles near their maximum blood volume capacity. Atrial systole will then occur, pushing the blood through the AV valves, filling the ventricles even more, increasing their pressure and volume. Next, as the ventricles begin to contract (ventricular systole), ventricular pressure (VP) rises above atrial pressure (AP), forcing the AV valves to shut. Since the semilunar valves are also closed, ventricular volume remains constant during this small period, known as Isovolumetric Contraction, causing a rapid increase in VP. When VP exceeds the pressure of the exit vessel (pulmonary artery and aorta for the right and left heart, respectively) the semilunar valves open, leading to the ejection of blood.

As the systole ends, the ventricular walls begin to relax (ventricular diastole) causing VP to drop drastically, falling below the exit vessel pressure, which causes the closure of semilunar valves. This period is referred to as Isovolumetric Relaxation because both semilunar and AV valves are closed, resulting in a constant ventricular volume and a further drop in VP. When VP falls below AP, AV valves open and blood flows into the ventricles, finally completing the cycle [10].

2.1.4 Heart Sounds

In a medical context the heart sound signal is collected from four main regions on the chest wall as demonstrated in Figure (2.4) .The aortic (A), between the second and third intercostal spaces at the right sternal border; mitral (M), near the apex of the heart between the fifth and sixth intercostal spaces in the mid-clavicular line; pulmonic (P), between the second and third intercostal spaces at the left sternal border; and tricuspid (T), between the third, fourth, fifth, and sixth intercostal space at the left sternal border [11].

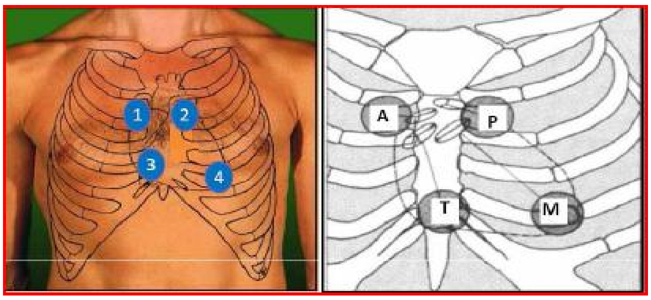


Figure (2:4): Auscultation Sites To Place Stethoscope. [11]

2.1.4.1 Mechanism of Heart Sounds production

Heart sounds can be heard throughout the heart cycle and are caused by several cardiac events such as ventricular filling, blood flow and, most of all, valve movements [10].

2.1.4.2 Heart Sounds categories

There are four main heart sounds, called S1, S2, S3 and S4. Normally, only two sounds are audible, S1 and S2 sounding like the words “lub – dub”. S3 and S4 are extra heart sounds heard in both normal and abnormal situations.

2.1.4.2.1 Normal heart sounds

The first sound S1 (lub) which corresponds to the R wave of the ECG, is longer in duration, lower frequency, and greater in intensity than the second sound. The closure of the mitral and tricuspid valve contributes largely to the first sound; so it marks the beginning of systole (end of diastole). The frequencies of this sounds are generally in the range of 30 to 100 Hz and the duration is between 50 to 100 ms; it loudest at the apex.

The second sound S2 (dub) is higher in pitch than the first, with frequencies above 100Hz and the duration between 25 to 50 ms. This sound is produced by slight back flow of blood into the heart before the valves close and then the closure of valves in the arteries leading out of the ventricles. This means that occurs at the closure of aortic and the pulmonary valves; so it marks the end of systole (beginning of diastole); it is loudest at the basic.

The heart also produces third and fourth sounds but they are much lower in intensity and normally inaudible. The third sound produced by the inflow of blood to the ventricles and fourth sound is produced by the contraction of the atria. These sounds are called diastolic sounds and are generally inaudible in normal adult but are commonly heart among children [12].

2.1.4.3 Abnormal Heart Sounds

• **Murmurs**

Are high-frequency, noise-like sounds that are heard between the two major heart sounds during systole or diastole. They are caused by turbulence in the blood flow through narrow cardiac valves or reflow through the atrioventricular valves due to congenital or acquired defects. They can be innocent, but can also indicate certain cardiovascular defects [11].

Murmurs are described as systolic or diastolic according to their timing in the cardiac cycle. Thus, a murmur heard after the first heart sound and before the second is a systolic murmur, and which comes after the second and before the first is a diastolic murmur [13].

• **Click and Snaps**

Are associated with valves opening and indicate abnormalities and heart defects. Opening snaps of the mitral valve or ejection sound of the blood in the aorta may be heard in case of valve disease (stenosis, regurgitation). The opening snap when present, occurs shortly after S2 with the opening of the mitral and tricuspid valves [11]. Clicks are short high pitched sounds, and have three types:

1. Ejection click: is the most common click, which occurs shortly after S1 with the opening of the semilunar valves [11].
2. Aortic ejection clicks.
3. Pulmonic ejection clicks.

2.1.5 Heart Failure and diseases

Heart failure is Inability of the heart to pump a sufficient amount of blood to metabolizing tissues or the ability to do so only with an increased filling pressure.

Heart failure is a syndrome that can be caused by different heart disease

In **coronary artery disease** (CAD), arteriosclerotic processes narrow the coronary arteries (that supply blood flow to the heart), and thereby restricting blood flow and adequate oxygenation of the myocardium. When the oxygen supply is insufficient to meet the oxygen demand the myocardium becomes ischemic, which may lead to infraction (tissue damage).

Hypertension is 'high blood pressure'. There is higher artery pressure against which the heart should inject.

Cardiomyopathy is a disease of the heart muscle. In most cases, cardiomyopathy causes the heart muscle to become weak.

There are two general types of cardiac valve defects:

Stenosis and insufficiency. Valvular stenosis results from a narrowing of the valve orifice that is usually caused by a thickening and increased rigidity of the valve leaflets, often accompanied by calcification. When this occurs, the valve does not open completely as blood flows across it. Valvular insufficiency results from the valve leaflets not completely sealing when the valve is closed so that regurgitation of blood occurs (backward flow of blood) into the proximal chamber.

Arrhythmia is a general term for different rhythm problems, including bradycardia, tachycardia, atrial fibrillation, ventricular fibrillation.

2.2 Stethoscope

A stethoscope is assist diagnostic instrument used by medical professionals to listen a patient's chest cavity, heart sounds and various pulse points.

Physicians use a stethoscope as part of a non-invasive examination procedure. Commonly, doctors will listen for sounds of congestion in the lungs and irregular heartbeats. Nurses may also use stethoscope to listen for restored flow during blood pressure checks.

2.2.1 Acoustic Stethoscope

For centuries, physicians would literally place their ears directly on a patient's chest or back as part of an examination, a procedure medically called 'immediate auscultation'. It was not unusual for doctors to contract communicable diseases through such intimate contact with sick patients. In the early 19th century, a young French physician named Rene Theophile Hyacinthe Laennec found examining female patient this way to be a little discomforting. In 1816, Dr. Laennec fashioned a cylinder from several sheets of paper and used it to examine a young female patient. He discovered that internal sounds could be insulated and amplified through a tube, making examinations less intrusive and easier to interpret [14, 15].

Figure (2.5): Laennec stethoscope. [15]

2.2.2 Electronic Stethoscope

The heart sound is usually detected by human ear using acoustical stethoscope but this is sometimes not efficient because of the limitations of the human's ear sensitively especially that heart sounds have low frequencies and low intensity, this fact was realized scientists and companies to develop the conventional stethoscope to be more sensitive and that led to inventing the electronic stethoscope.

The first electronic stethoscopes became available in by Albert Abrams; he developed a truly useable one, he was able amplify the sounds made by the heart. By applying resistance gradually to the circuit, he could eliminate certain sounds, thereby differentiating between the hearts muscular and valvular movements [16].

Electronic stethoscope has more advantages over the conventional stethoscope such as its sensitivity so that a variety of heart abnormalities can be traces by an electronic stethoscope; also it has more flexibility to deal with heart sounds by recording, processing the collected data and make a computer aided analysis and diagnosis. It can be expected that within a few years, the electronic stethoscope will have eclipsed acoustic devices.

Many of the Electronic stethoscope are designed by placing a microphone in the chest piece, another method, used in Welch-Allyn's Meditron stethoscope, comprises of a piezo-electric crystal at the head of a metal shaft, the bottom of the shaft making contact with a diaphragm. 3M also uses a piezo-electric crystal placed within foam behind a thick rubber-like diaphragm. Thinklabs' Rhythm 32 inventor, Clive Smith uses a like diaphragm with an electrically conductive inner surface to form a capacitive sensor. This diaphragm responds to sound waves identically to a conventional acoustic stethoscope, with changes in an electric field replacing changes in air pressure. This preserves the sound of an acoustic stethoscope with the benefits of amplification.

2.3 Literature Reviews

In the last decade, many research activities were conducted concerning automated and semi-automated heart sound diagnosis, regarding it as a challenging and promising subject. Many researchers have conducted research on the segmentation of the heart sound into heart cycles [17-19], the analysis and of the first and the second heart sounds and the heart murmurs [20], and also on feature extraction and classification of heart sounds and murmurs [21–23].

In this section some of papers will be represented as the following:

Automatic heart sound signal analysis with Reused Multi-Scale Wavelet Transform, by JiZhong and Fabien Scalzo, in International Journal Of Engineering And Science, March 2013,they proposed a method to locate S1 and S2 heart sound features effectively using a multi-scale wavelet transform and a threshold decision to increase the precision of the detection process. The effectiveness of the framework to extract the features is evaluated in experiments on 35 patients presenting various cardiac conditions. The proposed algorithm reaches an accuracy of about 92% on abnormal heart sounds and 100% on control [21].

Classification heart sounds based on the least squares support vector machine, by Gur Emre Gurak and Harun Uguz, which published in International Journal of Innovative during December 2011. In this study, primarily, heart sound signals in numerical format were separated into sub-bands through discrete wavelet trans-form. Next, the entropy of each sub-band was calculated by using the Shannon entropy algorithm to reduce the dimensionality of the feature vectors with the help of the discrete wavelet transform. The reduced features of three types of heart sound signals were used as input patterns of the least square support vector machines and they were classified least square support vector machines. In the method used, 96.6% of the classification performance was obtained [22].

Feature extraction from heart sound signal for anomaly detection, which is published in International Journal of Computer Science and Network

Security during September 2011. By Jeyarani and JayaSingh Thomas Gupta et al. determined the features of heart sounds by using wavelet transform. Heart sounds were classified into three categories by Grow and Learn network with a total performance of 96% [23].

Heart sound classification uses wavelet transform and incremental self-organizing map, by Zümray Dokur and Tamer Ölmez, which published during 2008, determined the features of heart sounds by using wavelet transform and principle component analysis. The heart sounds were classified into two categories by a neural network with a specificity of 70.5% and a sensitivity of 64.7% [24].

Wah W.Myint and Bill Dillard in their study at Collage of Engineering, Auburn University in USA applied an algorithm on two specific systolic murmurs, aortic stenosis and mitral regurgitation. The time-frequency analysis was performed using the (specgram) function in MATLAB which produces a local spectrum versus time. A spectrogram was produced for both murmurs and help in diagnosis [25].

Parameswary A.P.Renta in his thesis for Master degree from Electrical and Electronic Engineering Department, Collage of Engineering, University of Kejuruteraan and Technology in Malaysia during 2006; design an amplifier circuit which is used in electronic stethoscope (biomedical instrumentation). In his study he was focusing mainly on the operational amplifier which is used for multiple purposes. Basically the whole process is to amplify a small signal into a larger signal with reduced noise so that the output signal was amplified.. He mentioned that output was displayed in an oscilloscope to see the amplified signal [26].

Detection of heart murmurs using wavelet analysis and artificial neural networks, by N. Andrisevic, K. Ejaz, F.R. Gutierrez, R.A. Flores, They proposed algorithm which consists of three main stages. First; denoising of input data (digital recordings of heart sounds), via Wavelet Packet Analysis. Second; input vector preparation through the use of Principal Component Analysis and block processing. Third; classification of the heart sound using an Artificial Neural Network. Initial testing revealed the intelligent diagnostic system can differentiate between normal healthy heart sounds and abnormal heart sounds (e.g., murmurs), with a specificity of 70.5% and a sensitivity of 64.7% [27].

Analyzing heart murmurs using time-frequency methods, by P.R. White, W.B. Collis, A.P. Salmon, in: Proceedings of the IEEE-SP International Symposium, discussed methods developed heuristically based on a model of heart sounds, but their connection to existing techniques is also presented. The method exploits averaged versions of the Pseudo-Wigner-Ville distribution (PWVD). The algorithms are shown to detect two types of heart murmur and to be able to distinguish between them, a task which requires an experienced human listener [28].

2.3.1 Summary of literature reviews

In the literature reviews, it is observed that wavelet transform is frequently used to minimize noise and extract features of biological signals, and the most recent studies has been applied in off line data (data base).

In this study, a real time Heart Sounds Recognition system is using an electronic stethoscope to pick up signals from patient directly in a real time, and transmitted it to PC to be processed, analyzed and classified.

CHAPTER THREE

DESIGN AND IMPLEMENTATION

3.1 Introductory

This chapter discusses the design and implement of a real time heart sounds recognition system, which integrated into two phases (offline data phase and experimental real time phase).

3.2 Phase one: (off line data)

In this phase, 30 data files of heart sounds with different cases (aortic stenosis, atrial fibrillation, aortic regurgitation, mitral fibrillation…etc) were collected from medical students and doctors world website [29]. Then the algorithm has been applied to process and analysis data.

The proposed algorithm includes three major stages i.e., preprocessing, feature extraction, and classification, the respective descriptions of which are provided in the following sections.

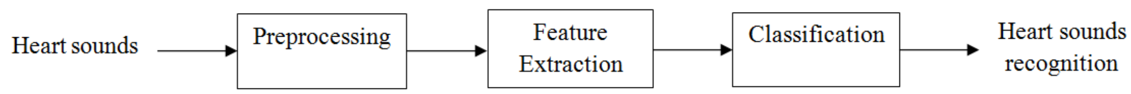


Figure (3.1): Block Diagram of system Algorithm

3.2.1 Preprocessing

The purpose of this step is to eliminate noise and enhance heart sounds by de-noising process.

De-noising

High quality signals are essential for correct recognition. Unfortunately, the presence of noise in heart sounds signals is inevitable. Even when all background noise is minimized there are always intrinsic sounds impossible to avoid such as respiratory sounds, muscular movements and air flow.

Therefore, the de-noising stage is extremely important, ensuring elimination of noise and emphasizing relevant sounds [10].

Due to the overlapping nature of noise with the spectra of the heart sounds signal, simple analogue filters are not effective for noise reduction. However, decomposing the signal in narrower sub-bandwidths using the wavelet transform. This enables the temporal noise reduction for the desired bandwidth sections [11]. The mother wavelet implemented here is the Debauches wavelet of order 5 (db5) figure (3.2). The choice is due to the heart beat signal having most of its energy distributed over a small number of db5 wavelet (scales), and therefore the coefficients corresponding to the heart beat signal will be large compared to any other noisy signal figure (3.3) [30]. The de-noising procedure involves three steps:

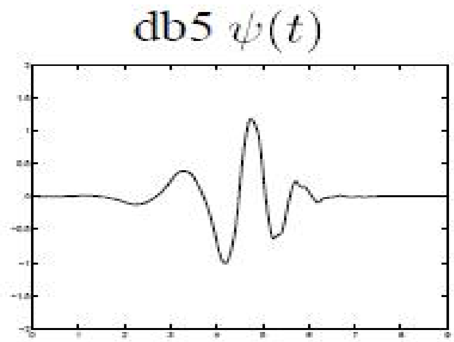


Figure (3.2) Debauches 5 (db5)

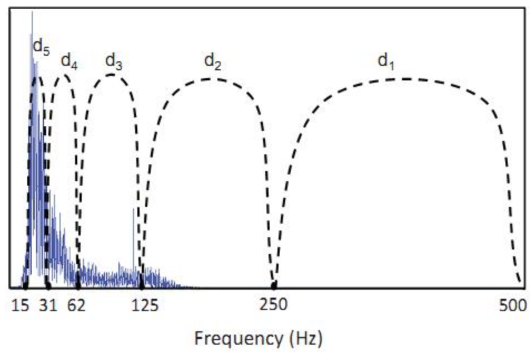


Figure (3.3) Equivalent frequency responses of the DWT, over the heart sounds spectrum.

I. Decomposition

The heart sound in this step is divided into approximations and details, where the approximations represent the slowly changing (low frequency-high scale) features of the signal and details represent the rapidly changing (high frequency– low scale) features of the signal [30].

A decomposition of level 5 with the (db5) wavelet was selected for the decomposition part of the de-noising algorithm.

II. Thresholding detailed coefficients

This step involves thresholding the detailed coefficients of the DWT and then reconstructing the signal with the inverse discrete wavelet transform (IDWT). There are two common methods for thresholding; soft thresholding and hard thresholding. The method chosen is the soft thresholding, where it produces better result than hard thresholding because it sets the elements whose absolute values are lower than the threshold to zero and then the nonzero coefficients remaining are shrunk and set to zero. In the other hand hard thresholding sets the elements whose absolute values are less than the threshold to zero.

III. Reconstruction

The last step in the de-noising procedure is to compute the wavelet reconstruction through the summation of the original approximation coefficients of the last level (level5) and the modified detail coefficients of levels 1 to 5 [30].

3.2.2 Features Extraction

The heart sounds is non-stationary signals and have features in both time and frequency domain, some of them are statistics features such as (mean, standard deviation, kurtosis, and variance), and others are graphical features such as (spectrogram and power spectrum).

3.2.2.1Graphical representation features

In the time domain, heart sounds (HSs) have to be represented graphically; amplitude versus time. However, discriminatory information can be found in the frequency-domain.

Spectrogram

Spectogram is a time-varying spectral representation that plots the variation of spectral density with respect to time. Spectrogram is a two dimensional graph, where horizontal axis represents time and vertical axis represents frequency. A third dimension indicating amplitude of a particular frequency is represented by the intensity or color of each point in the signal.

Power spectrum

From power and energy prospective, signals can be classified into three broad categories, power signals, energy signals, or both. Heart sound signals also have finite average power and fall into the category of power signals shown in figures (4.6a, 4.13a, 4.7b, and 4.14b).

3.2.2.2 Representation of measured and calculated parameters

For numerical values, the presentation of the results appears in Table [4.1], and Table [4.3] containing Kurtosis, Standard deviation, variance and mean absolute value.

Kurtosis is gives the degree of peakedness of a probability distribution.

Mean is sum of absolute mean of wavelet coefficients.

Standard deviation related to deviation from mean and equal to sum of absolute standard deviation of wavelet coefficients and Variance Returns the variance of data from mean value.

3.2.3 Classification process

Euclidean distance

Euclidean distance is the distance between two points, determines by:

(3.1)
$$d(p,q) = \sqrt{\sum_{i=1}^{n} (p_i - q_i)^2}$$

Where, d is Euclidean distance, p and q are the arrays and n is the dimension of arrays [31].

The distance (error) of power spectrum density (PSD) is calculated between reference signal (control) and sample signal by using Euclidean distance.

In this stage the statistics features of the sample sound such as (mean, variance, kurtosis, and standard deviation), and Euclidean distance error for PSD, were compared with threshold and features that stored in the database (control), and look-up table was applied to classify cases into normal and abnormal.

3.3 Phase Two: Experimental designing and implementation (real time data)

This section discusses the integrated system for experimental phase, real data was recorded directly from patient (online data), and realized the algorithms that applied in phase one (offline data phase).

As illustrated in block diagram bellow:

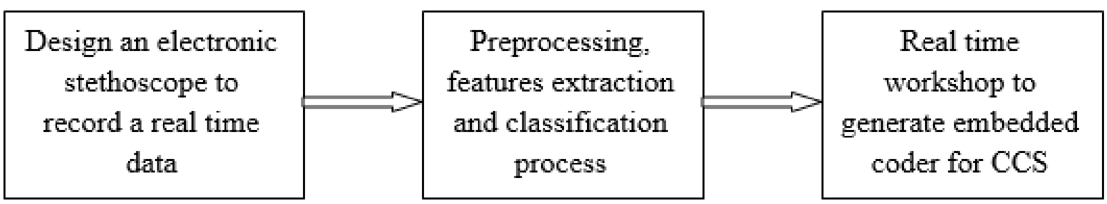


Figure (3.4) general block diagram for Experimental phase (real time data)

This section consists of three steps:

1. **Step one**: Design an electronic stethoscope system to record signal directly from patient as the real time, and then transmit it to PC to be analyzed and processed.

2. **Step two**: This step discusses the implementation using MATLAB software. The decision-making process comprises of three main stages. At the preprocessing, heart sounds are filtered from lung sounds by applying adaptive filter LMS. DWT used to minimize background noise. Then the, feature vector elements are formed by using statistics and graphical features. Finally, classification process was accomplished by look-up table.

3. **Step three**: Convert script file (m.file) to embedded Coder.TLC to be compatible with Code Composer Studio (CCS) software.

All these steps are described in details bellow:

3.3.1 Step one: Design of an Electronic Stethoscope

The system basically consists of:

1. Stethoscope electrode (sensor)
2. Microphone in frequency response range (30-20kHz)
3. Signal conditioning (amplification and filtration)
4. Speaker to listen sound and LED as alarm

As illustrated in block diagram below:

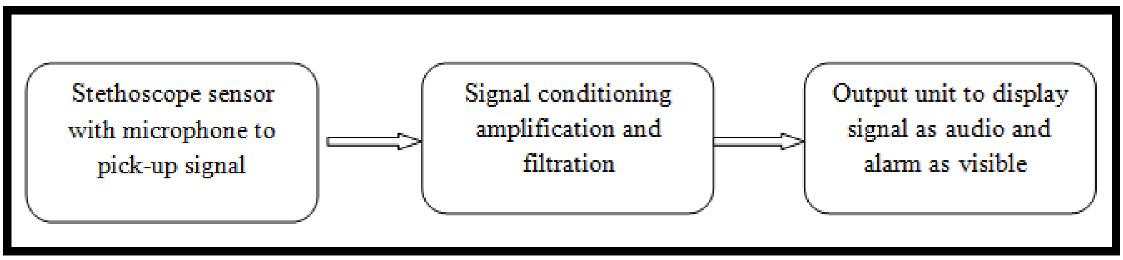


Figure (3.5): general block diagram of electronic stethoscope

3.3.1.1 Stethoscope sensor and microphone

Stethoscope sensor is a device used to measure the heart sounds and converts biological signal to an electric signal.

The microphone has Frequency response range (30Hz to 20 KHz) that can detect heart sounds clearly [32].

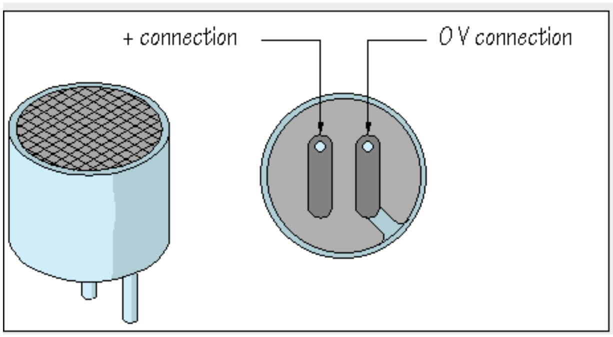


Figure (3.6): the microphone. [32]

3.3.1.2 Operational amplifier (op-amp):

Operational amplifier is an electronic piece have high impedance at the input terminals (ideally infinite), and low output impedance (ideally zero) [33].

Operation amplifiers mostly used in signal conditioning stages to amplify and filter signal from noise.

Since heart sounds are very week in amplitude and low in frequency, op-amps are used to amplify and filter heart sounds.

The op-amp (TL072) was selected to amplify and filter HSs due to the following specification:

TL072 has Low power consumption, Wide common mode and differential voltage ranges, Low input bias and offset currents, Low total harmonic distortion …0.003% Typ, High input impedance JFET input stage, Internal frequency compensation and Common-mode input voltage range includes Vcc.

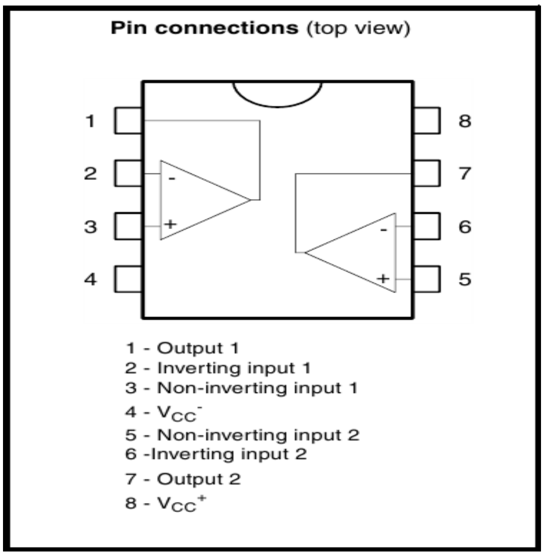


Figure (3.7): pin configuration of operation amplifier (TL072).

3.3.1.3 Electronic Filters

Electronic or active filters are electronic circuits which perform signal processing functions, specifically to remove unwanted frequency component from the signal [33].

Using low pass filter which passes frequency lower than cut off frequency and eliminate all frequencies high than cut off frequency; but this is ideal and not real, the real low pass filter can't filtering all frequencies that above the cut off frequency, but attenuate them.

The second order low pass filter with a cut off frequency of (103Hz) was used.

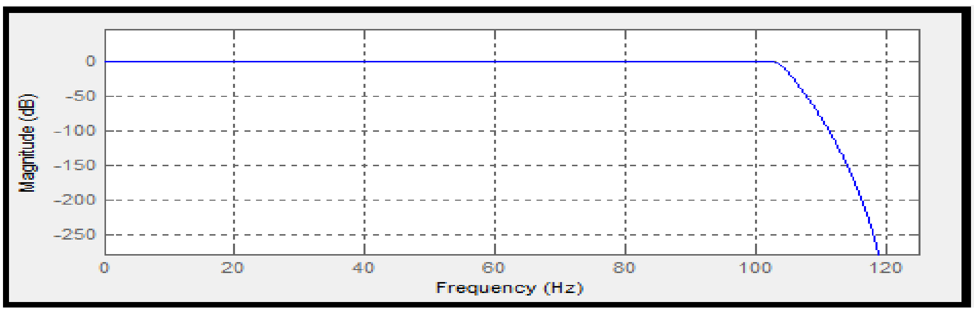


Figure (3.8): frequency response for second order LPF (fc=103Hz).

3.3.1.4 The Output Units

Using an audio amplifier (LM386) and stereo headphone to listen sounds as audible and LED as visible indicator.

The integrated circuit diagram has been described as figure bellow:

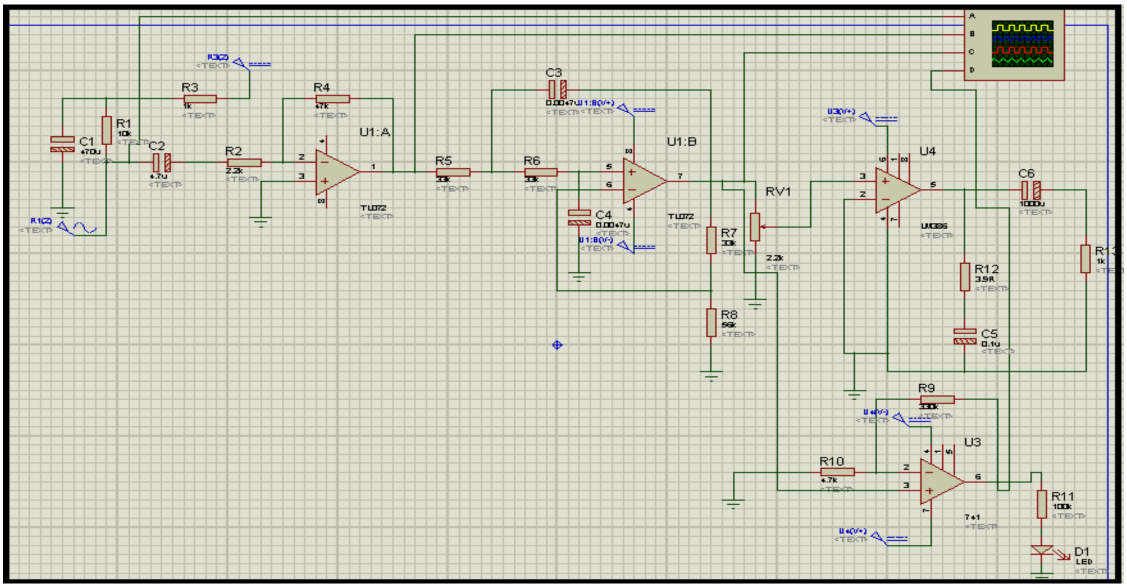


Figure (3.9): shows the integrated circuit diagram of Electronic stethoscope

Circuit Description:

- U1a operates as a low-noise microphone preamplifier. Its gain is only about 3.9 because the high output impedance of the drain of the FET inside the microphone causes U1a is effective input resistor to be about 12.2K. C2 has a fairly high value in order to pass very low frequency (about 20 to 30Hz) heartbeat sounds.

- U1b operates as a low-noise reduction, Butterworth 2nd order low pass filter with a cutoff frequency of about 103Hz. R7 and R8 provide a gain of about 1.6 and allow the use of equal values for C3 and C4 but still producing a sharp Butterworth response.

- The U3 circuit is optional and has a gain of 71 to drive the bi-color LED.

U4 is a 1/4W power amplifier IC (LM386) with built-in biasing and inputs that are referred to ground. It has a gain of 20. It can drive any type of headphones including low impedance (8 ohms) ones.

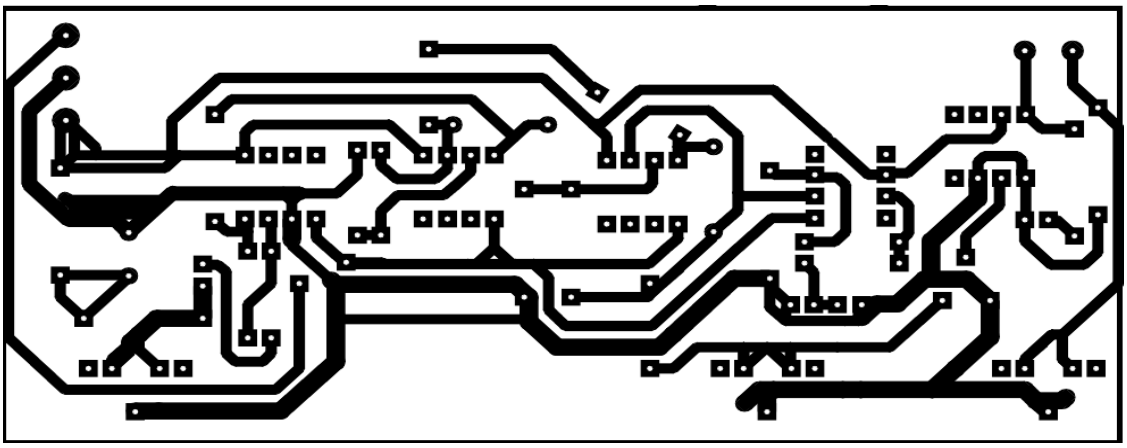


Figure (3.10): shows the integrated PCB circuit of an electronic stethoscope.

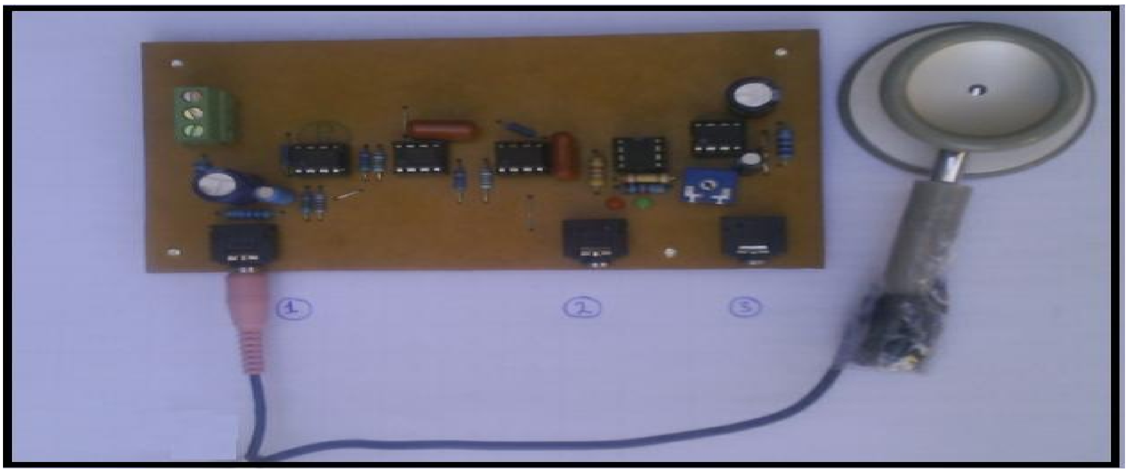


Figure (3.11): shows the implemented circuit of an electronic stethoscope

- Label 1: indicates to input source of stethoscope.
- Label 2: indicate to output which interfaced circuit with PC via Jack as data transfer.
- Label 3: indicate to output which transmitted to stereo headphone.

The output voltages for first and second stages are compatible to be accepted and read as input signal for PC mic. Then, circuit is interfaced with PC via (Jack) as data transfer, and a SIMULINK model is created to identify the input source such as the following.

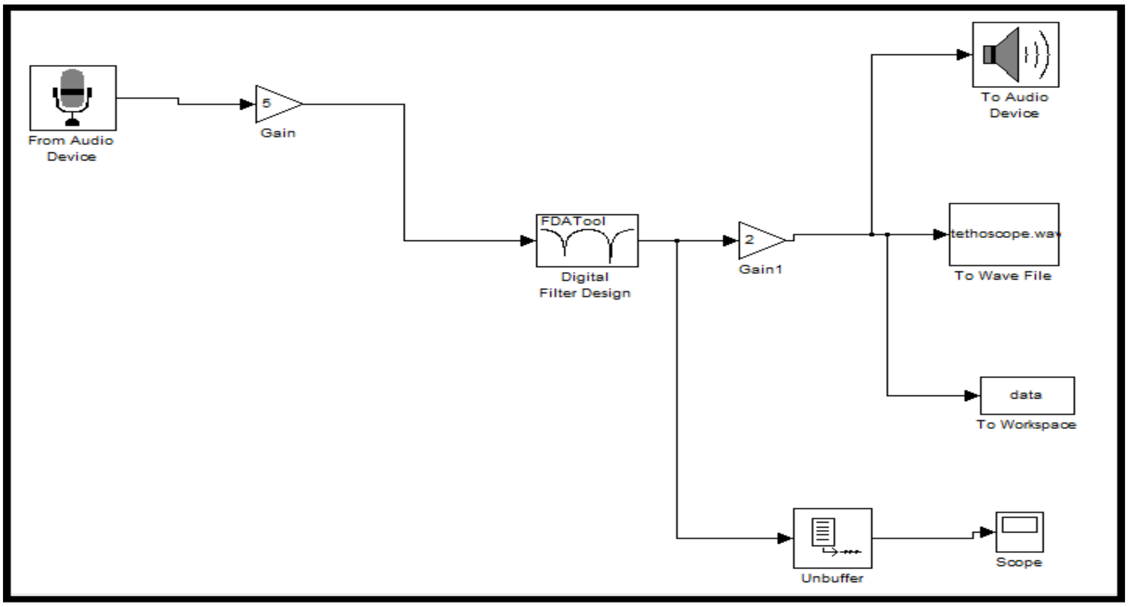


Figure (3.12): SIMULINK Model for input Source Identification.

MATLAB SIMULINK program is used to perform:

- Reading audio data from an audio device in a real time (from audio device block).
- Give gain (5) and gain1 (2).
- Filter signal from noise by using digital filter block (low pass filter with F_{pass}=103Hz, F_{stop}=110Hz).
- Record the sound in .wave format (to wave file block).
- Send the sounds to PC audio device (to audio device block).
- Send recorded data to MATLAB workspace (to workspace block).
- Display the sound samples in oscilloscope (scope block).

3.3.2 Step Two: Preprocessing, Features extraction, and classification for recorded electronic stethoscope output waves

This step consist four stages as the following:

3.3.2.1 First stage: lung sound cancellation using Adaptive filter:

The heart sounds and lung sounds have common sub band frequencies, the frequency of HSs is (30 to 110Hz) where the lung frequency is (100 to 600Hz) [5].

The feature of heart sounds may be impure by lung sounds because the lung and the heart sound overlap in terms of time domain and spectral content. Low pass filtering (LPF) with an arbitrary cut-off frequency 100 Hz is not efficient in this case, because heart sound have major components in that region particularly at above 100 Hz. If we used the advanced Digital Signal Processing more flexibility, it removes the lung sounds and predicts the gaps successfully.

There are different methods can be applied for filtering lung sound from heart sound recordings: wavelets, independent component analysis, adaptative filtering with recursive least squares algorithm (RLS), adaptive filtering with least mean square algorithm (LMS) [34].

In this research an adaptive filtering with least mean squares algorithm (LMS) was used Figure (3.13). Adaptive filters adjust their values to achieve the desired result. It does not require any other frequency response information or specification and can be used to filter lung sound from heart sound without altering the main characteristic features of heart sounds [35].

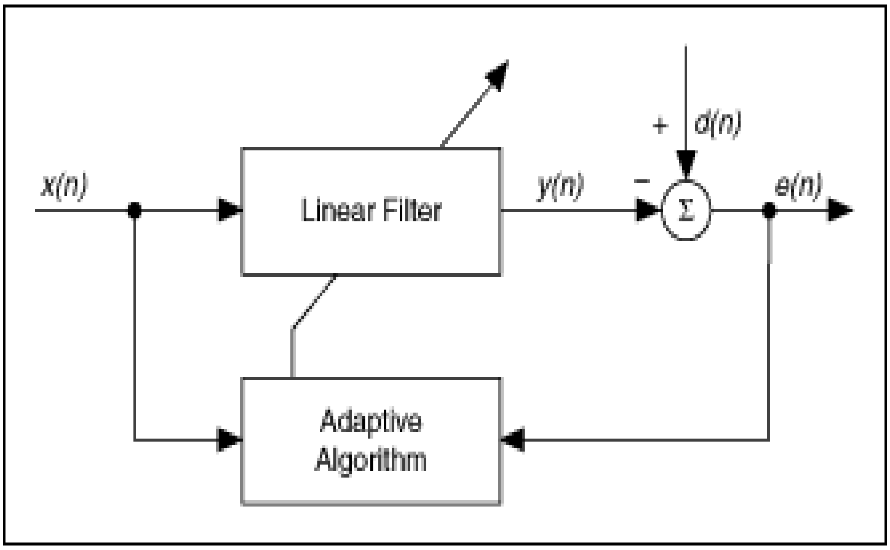


Figure (3.13): Adaptive filter structure. [34]

Symbols:

(As they pertain to lung sound cancellation from heart sound): d(n)=heart sound; x(n)=reference lung sounds; y(n)=adaptive filter output; e(n)=de-noised heart sounds.

The methods which are discussed here are not fully free from the artifacts of the lung sounds [34].

3.3.2.2 Second stage: minimized background noise using wavelet transform and soft threshold denoisng.

Record in hospital by any type of sensor is affected by environmental noise, and other physiological sound e.g. (muscles moving, blood flow, etc…). Remove these type of noise without loses in signal component is very difficult.

Nonparametric analysis such as Fast Fourier transform (FFT) has a serious drawback. When transforming to the frequency domain, time information is lost, and when looking at Fourier transform of a signal, it is impossible to tell when a particular event took place.

Signals usually contain both low frequency components and high frequency component. High frequency component vary quickly with time and require fine time resolution but coarse frequency resolution .Multi-resolution analysis (MRA) method is used to analyze a signal that contains both low and high frequency components.

Wavelet signal processing is naturally an MRA method because of the dilation process. The DWT is well-suited for multi-resolution analysis. The DWT decomposes high-frequency components of a signal with fine time resolution but coarse frequency resolution, and decomposes low frequency components with fine frequency resolution but coarse time resolution; which make it a beneficial tool for de-noise and feature extraction applications for non-stationary signals.

Therefore, discrete wavelet transform (DWT) was used to minimized back ground noise (wavelet de-noise). (Such as phase one in this chapter).

3.3.2.3 Third Stage: feature extraction

Extract signal features in both time and frequency domain (graphically and statistics features), which applied in phase of offline data.

3.3.2.4 Fourth Stage: classification process

Classify signal into normal and abnormal cases (using look-up table), which was applied in the offline data as well.

3.3.3 Step three: Convert script file (m.file) to embedded coder

To convert m.file to embedded coder.tlc; firstly, convert m.file code to SIMULINK model, then using Real Time Workshop (RTW) to generate embedded coder.tlc which is compatible with Integrated Development Environment (IDE) software called Code Composer Studio (CCS).

3.3.3.1 Code Composer Studio (CCS):

Texas Instruments (TI) facilitates development of software for TI DSPs by offering Code Composer Studio (CCS) Integrated Development Environment (IDE). Used in combination with Target Support Package software and Real-Time Workshop software, CCS provides an integrated environment that, once installed, requires no coding.

Executing code generated from Real-Time Workshop software on a particular target requires that you tailor the code to the specific hardware target. A target-specific code includes I/O device drivers and interrupts service routines (ISRs). The software must use CCS to compile and link the generated source code in order to load and execute on a TI DSP. To help you to build an executable, Target Support Package software uses Embedded IDE Link™ software to start the code building process within CCS. After you download your executable to your target and run it, the code runs wholly on the target. You can access the running process only from the CCS debugging tools or across a link using Embedded IDE Link software [36].

Figure (3.14): Code Composer Studio v5.1 Icon

CCS project have the following types of files:

- **.lib** This TI library provides runtime support for the target DSP chip
- **.c** This file contains source code that provides the main functionality of this project
- **.h** This file declares the buffer C-structure as well as define any required constants
- **.pjt** This file contains all of your project build and configuration options
- **.asm** This file contains assembly instructions
- **.cmd** This file maps sections to memory

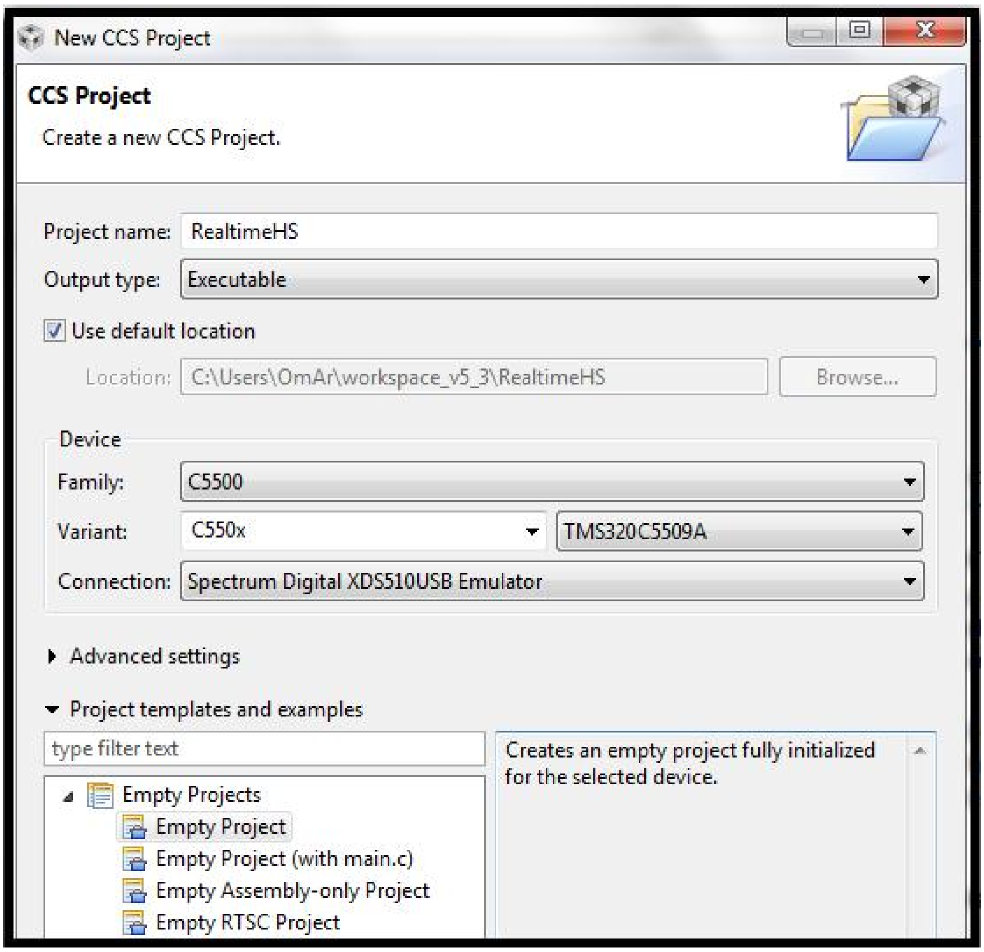


Figure (3.15): show how to create project on CCS software

3.3.3.2 Simulation of Hardware design flow

The three steps involved in simulation of hardware design flow are described below.

I. Convert m.file to SIMULINK model

SIMULINK model is generated by using the appropriate tool boxes from the SIMULINK Library Browser.

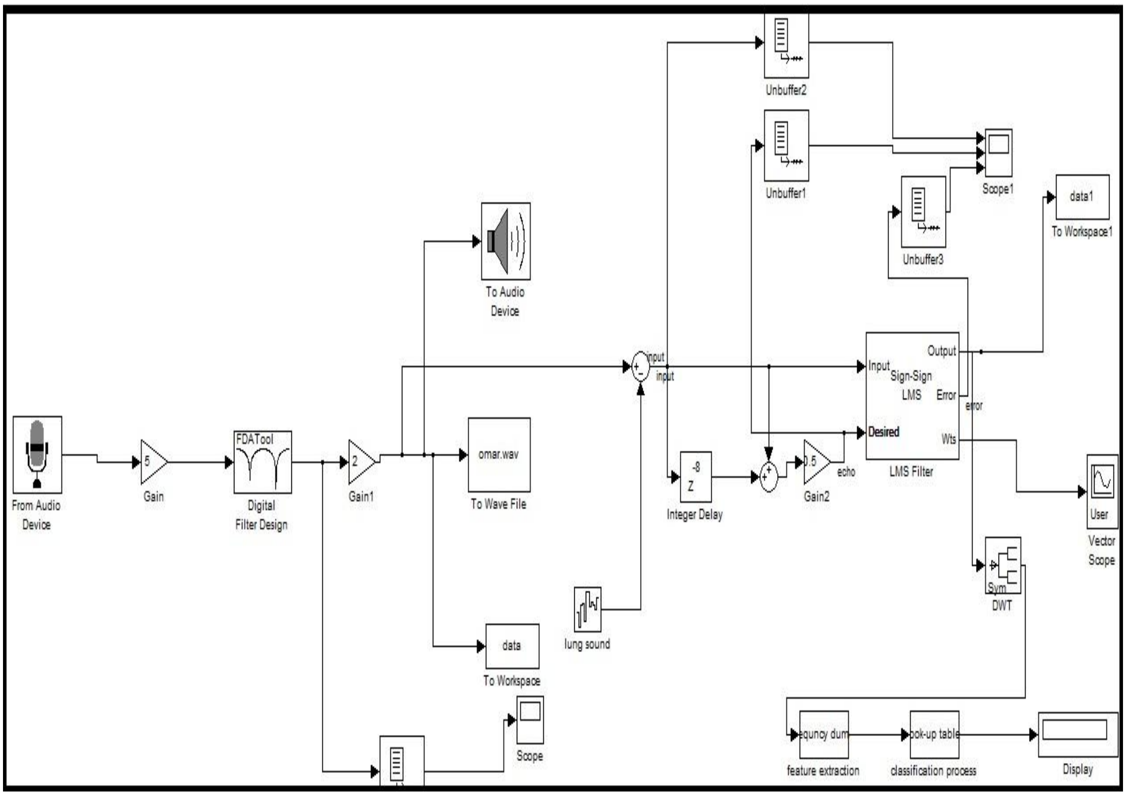


Figure (3.16): show integrated SIMULINK of system model

II. Selecting an Embedded Code Target

Configure the Real-Time Workshop Embedded Coder software to generate code for one of a variety of targets using code generation options and parameters. The options and parameters are consolidated in the configuration set of the model, which you can view in the standalone Configuration Parameters dialog box or in the SIMULINK Model Explorer.

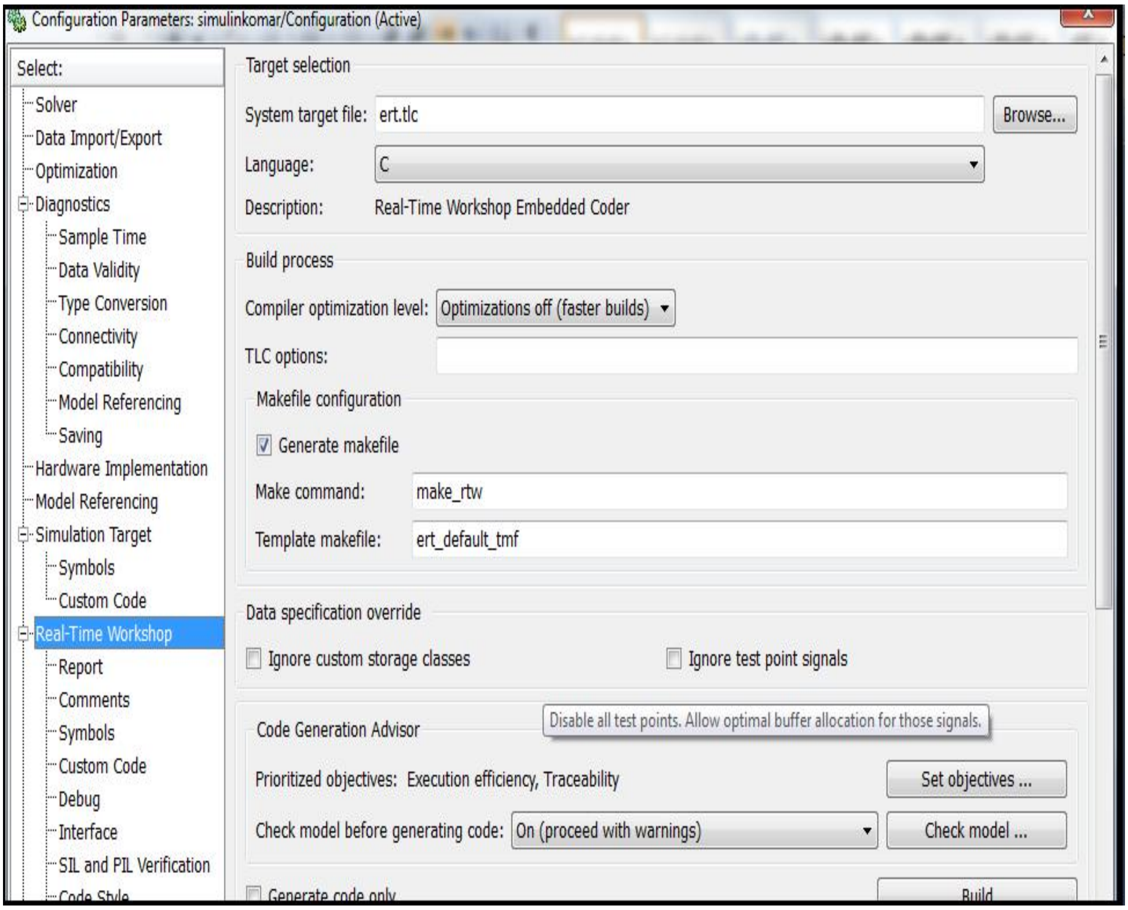


Figure (3.17): show the configuration parameters simulation

III. Configuring Code Generation Options Based on High-Level Objectives

The Embedded Real-Time (ERT) target includes a utility to quickly specify and prioritize code generation settings based on your objectives, such as Execution efficiency, ROM efficiency, RAM efficiency, Traceability, Safety precaution, and Debugging. Once specified, you run the utility to establish settings and identify changes based on the objectives. You can check whether the model meets your objectives by clicking **Check model**, or check the model during the code generation build process by setting **Check model before generating code** to On. The checks are provided within the SIMULINK Model Advisor.

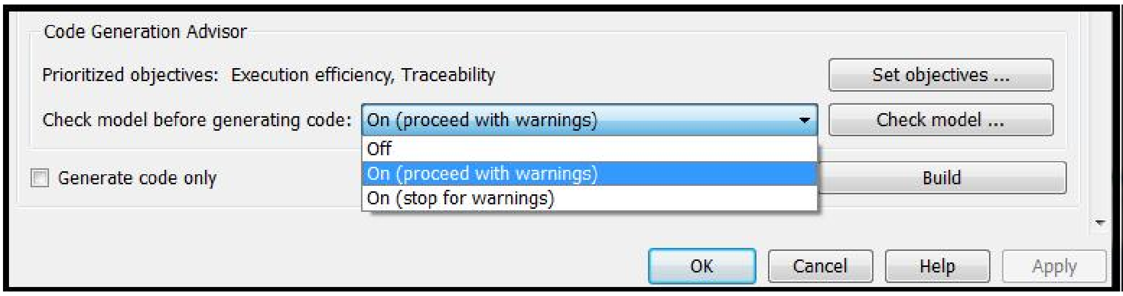


Figure (3.18): show how to check code generation advisor

3.3.3.3 Generating Code and Viewing the Artifacts

Click **Build** to generate code. After code generation is complete, a detailed code generation report opens. The report includes links to the generated code and associated artifacts, including:

1. Source code and header files
2. Code interface report (global data and functions)
3. Traceability report (accounting for all the objects in the model)
4. Validation report (result of the code generation objective checks)

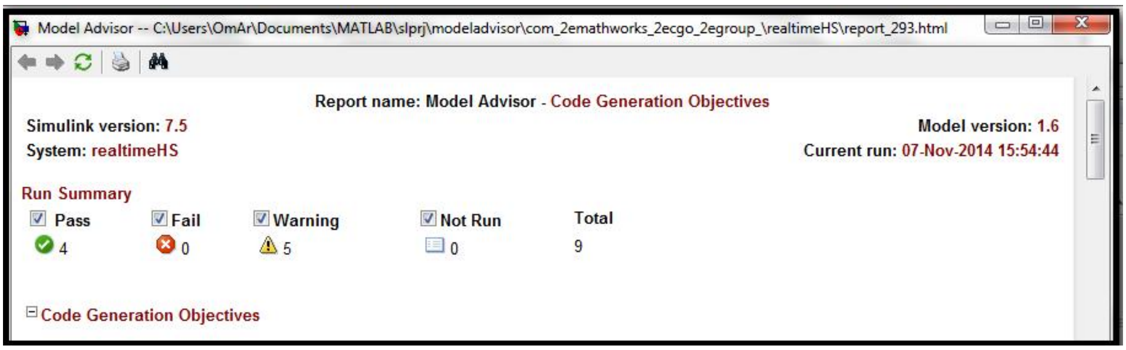


Figure (3.19): show report of code generation

CHAPTER FOUR

RESULTS AND DISCUSSIONS

4.1 RESULTS A: OFFLINE DATA

The algorithm has been applied for offline data which Collected 30 data of heart sounds with different cases (aortic stenosis, atrial fibrillation, aortic regurgitation, mitral fibrillation..., etc) from medical students and doctors world website [29]. In preprocessing stage, wavelet transform was applied, and wavelet coefficients are determined by using Daubechies-5 as a mother function, level 5 for each heart sound signal. Then used (soft) thresholding wavelet de-noising .And then extract features graphical and measurable calculated features, which selected in classification process to distinguish between these signals (normal or abnormal) .

4.1.1 Normal Heart Sound:

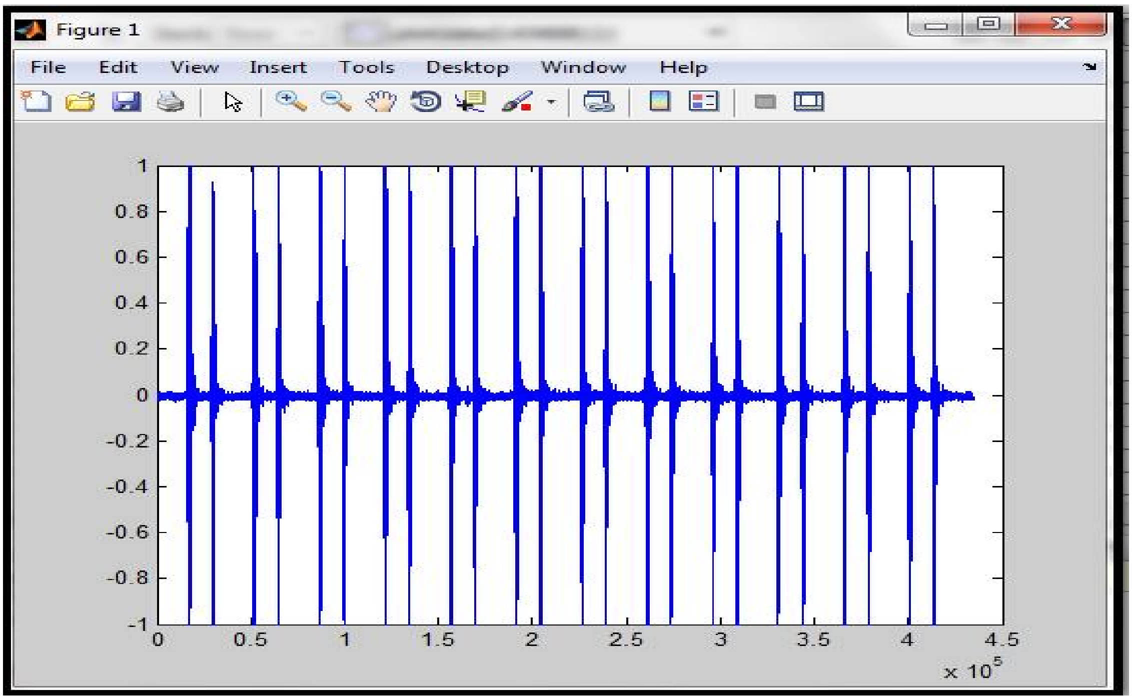


Figure (4.1a): original signal of normal heart sound.

Wavelet decomposition

Computed DWT using db5, level five shown in Figure (4.2a)

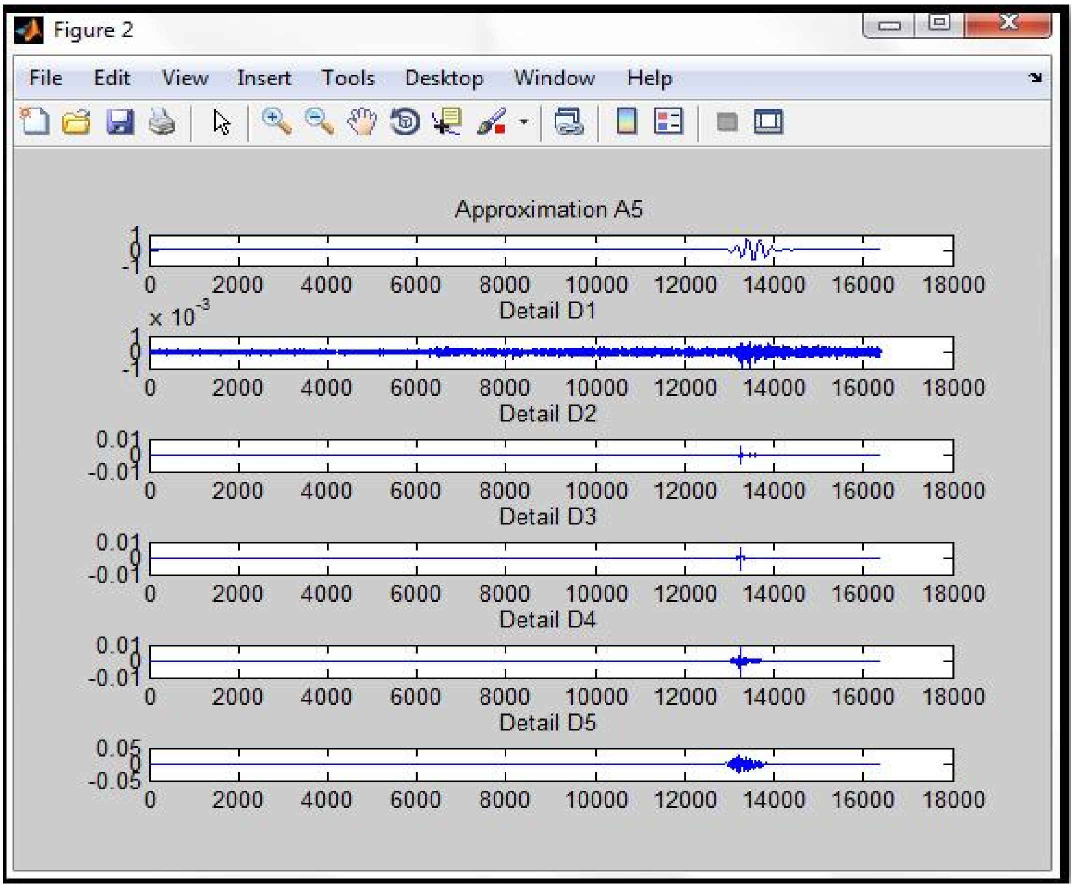


Figure (4.2a): wavelet coefficients using db5.

In wavelet analysis, a signal is split into an approximation (A) and a detail (D). The approximation is then itself split into a second-level approximation and detail, and the process is repeated. For the above figure the signal was decomposed into 5-level (D1, D2, D3, D4, D5, and A5).

Wavelet reconstruction

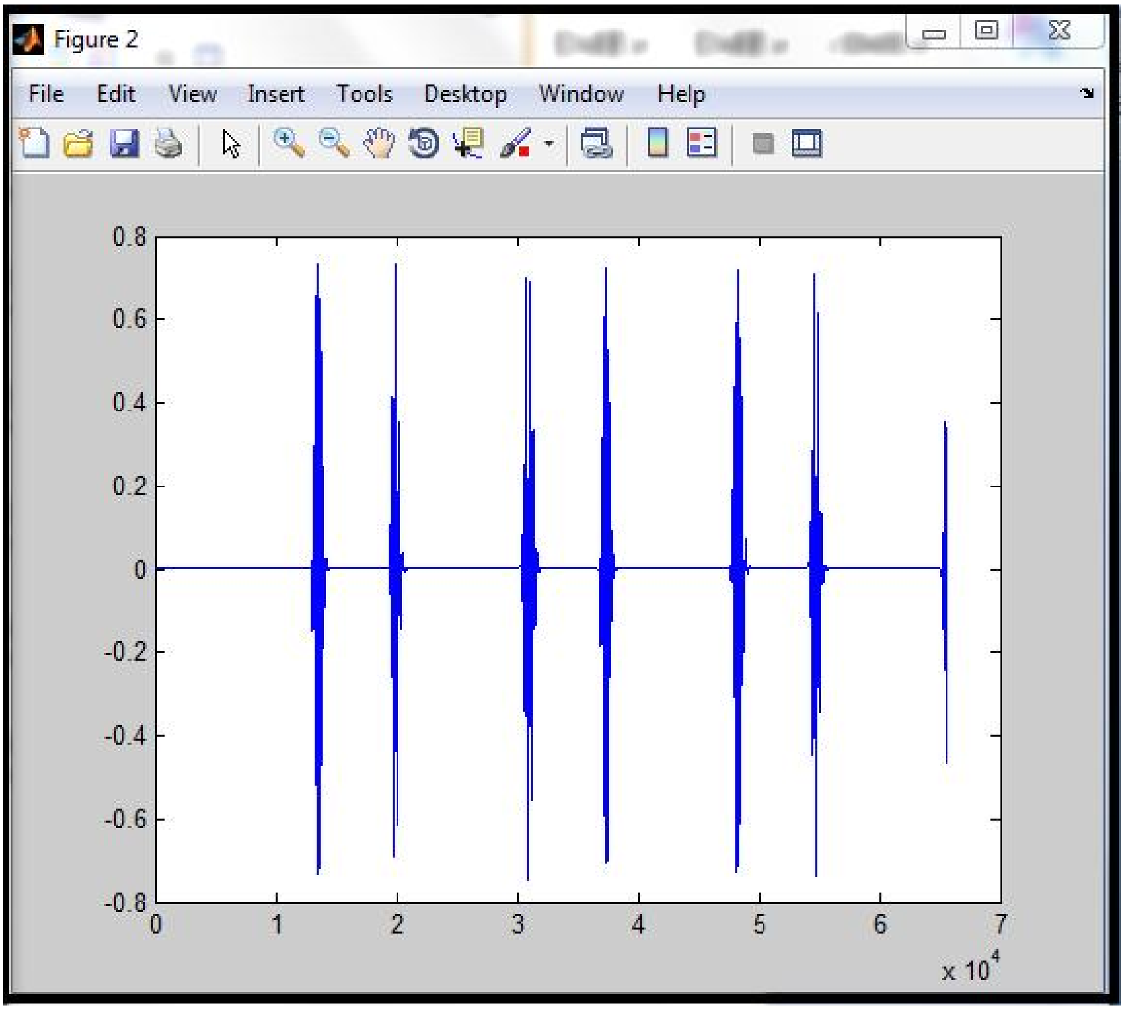


Figure (4.3a): signal for combination wavelet coefficients.

The figure interprets the other half of the wavelet transform, by how those components can be assembled back into the original signal with no loss of information. This process is called reconstruction, or synthesis. The mathematical manipulation that effects synthesis is called the inverse discrete wavelet transform (IDWT). The figure (4.3a) show how to combination wavelet coefficient through the summation of the original approximation coefficients of the last level (level5) and the modified detail coefficients of levels 2 to 5.

For de-noising signal

Of course, in discarding all the high-frequency information, we have also lost many of the original signals sharpest features. Optimal de-noising requires a more subtle approach called soft thresholding. This involves discarding only the portion of the details that exceeds a certain limit.

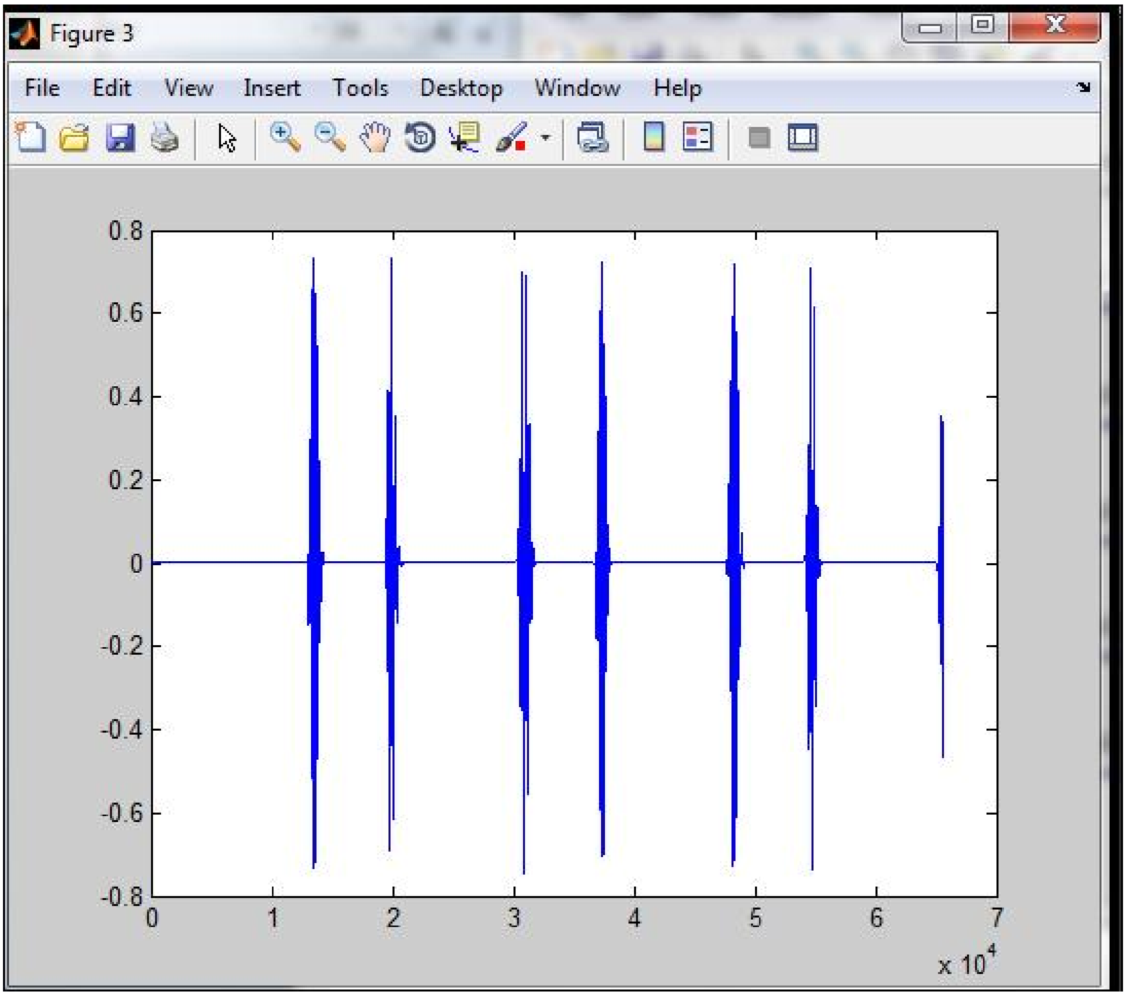


Figure (4.4a): soft threshold to de-noising signal.

The method chosen here is the soft thresholding, where it produces better result than hard thresholding because it sets the elements whose absolute values are lower than the threshold to zero and then the nonzero coefficients remaining are shrunk and set to zero.

The Spectrogram of signal

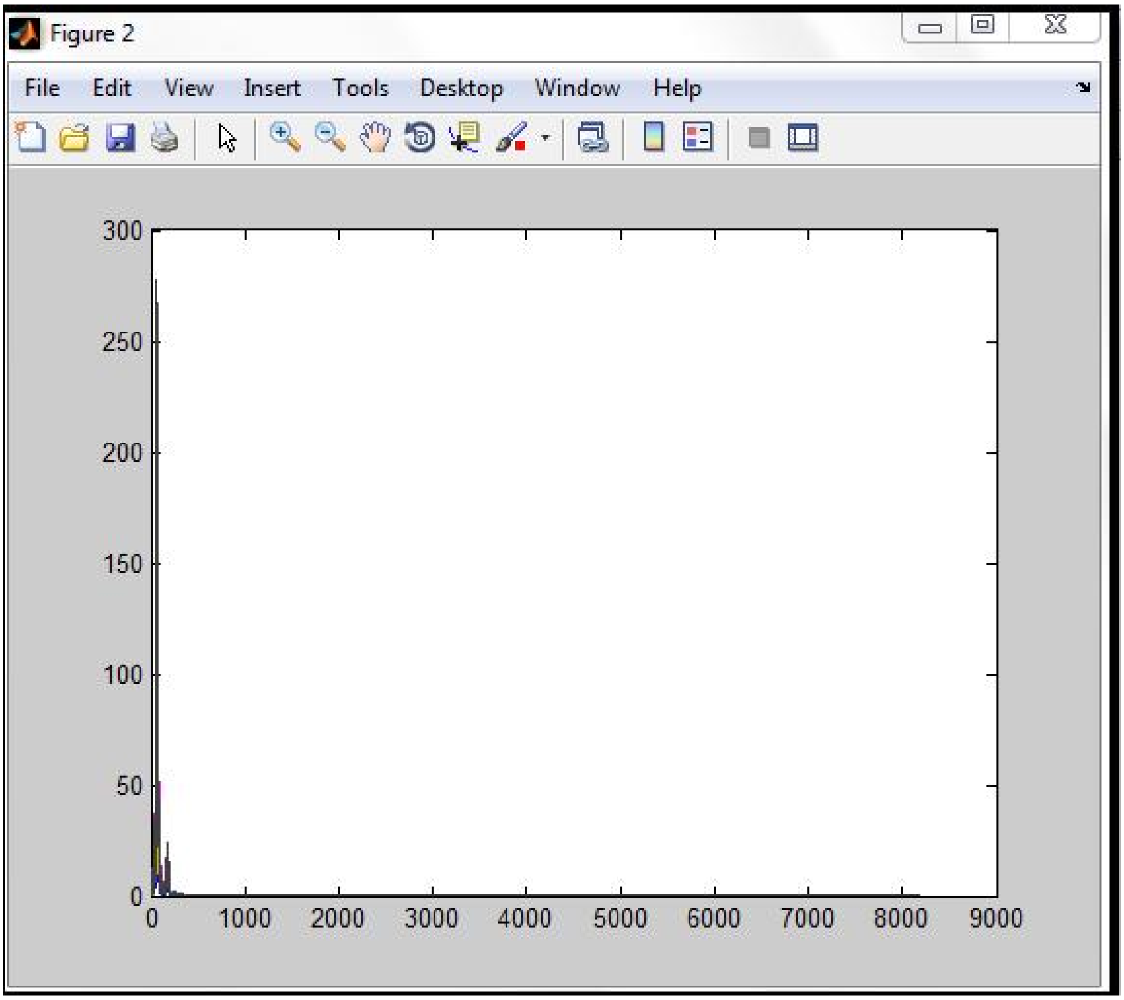


Figure (4.5a): spectrogram of the processed signal

Spectrogram is a time-varying spectral representation that plots the variation of spectral density with respect to time. Spectrogram is a two dimensional graph, where horizontal axis represents time and vertical axis represents frequency. A third dimension indicating amplitude of a particular frequency is represented by the intensity or color of each point in the signal.

The signal Power Spectrum Density (PSD)

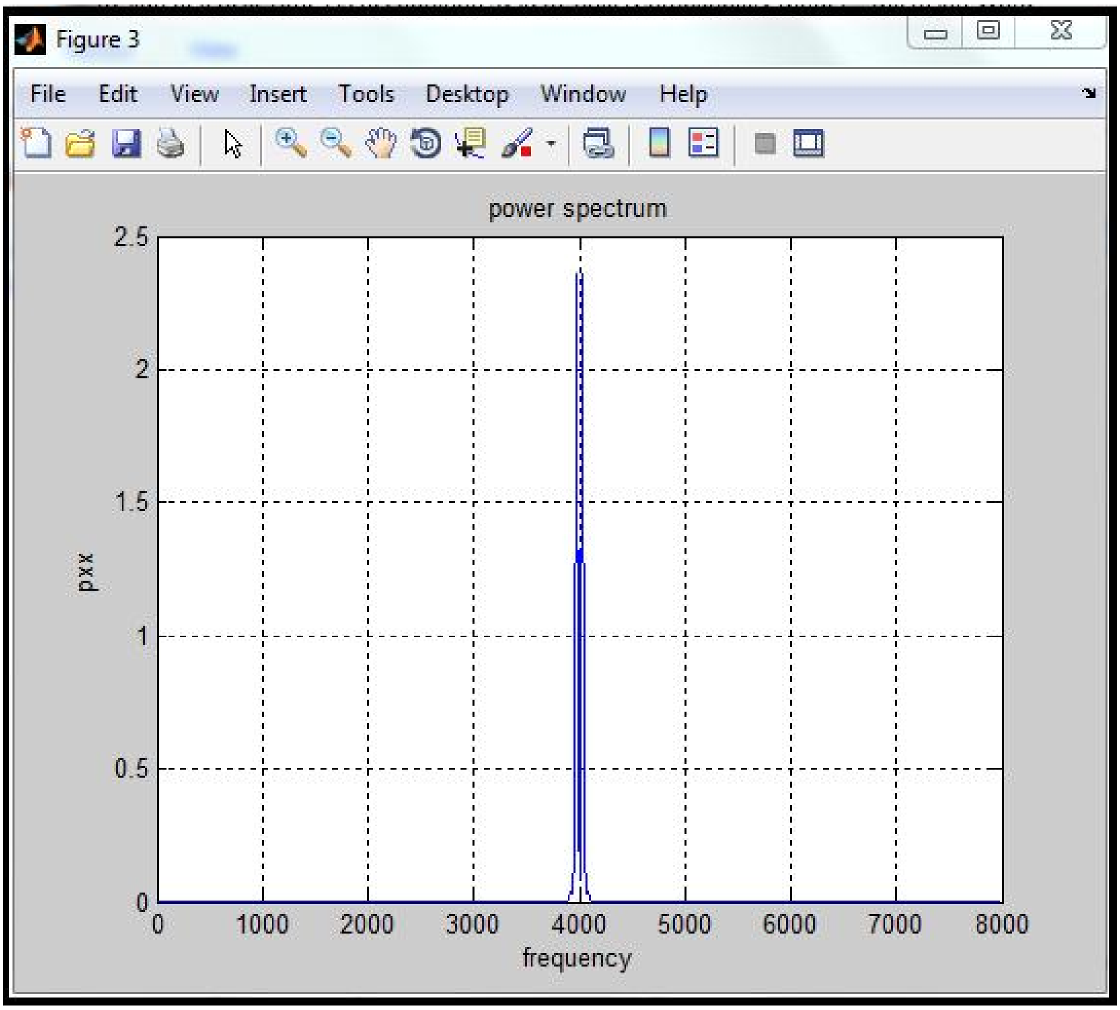


Figure (4.6a): power spectrum of the signal

The power spectrum density of a signal gives the distribution of the signal power among various frequencies.

It has been observed the peak value of PSD in normal case is less than abnormal case, due to intensity of abnormal case is highest than normal case.

Classification process

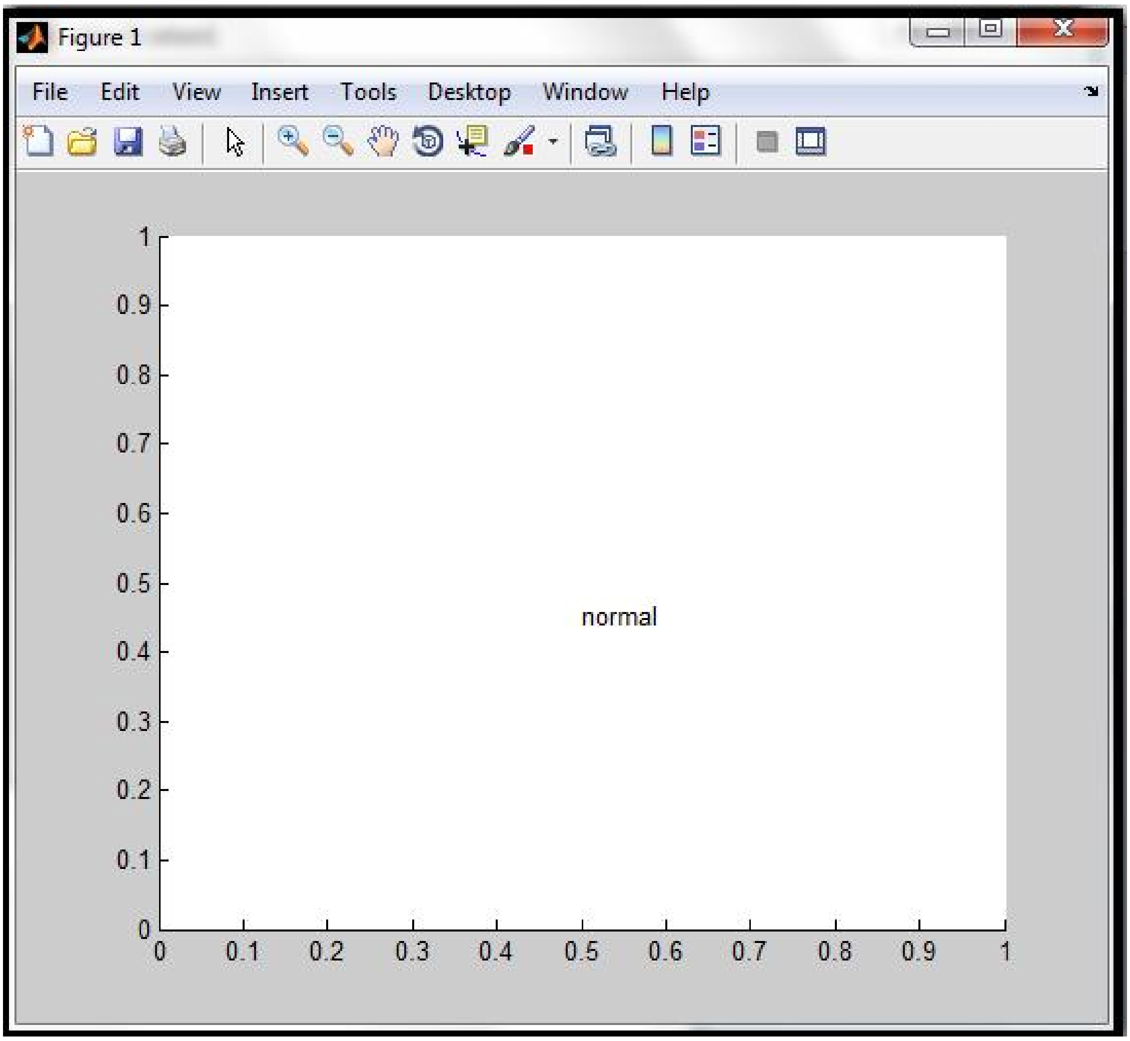


Figure (4.7a): illustrates the classification of the signal

In the classification process the statistics features of the sample sound such as(mean, variance, kurtosis, and standard deviation) and Euclidean distance error for PSD, were compared with threshold and features that stored in database (control), and look-up table was applied to classify cases into normal and abnormal.

4.1.2 Abnormal Heart Sound (murmur):

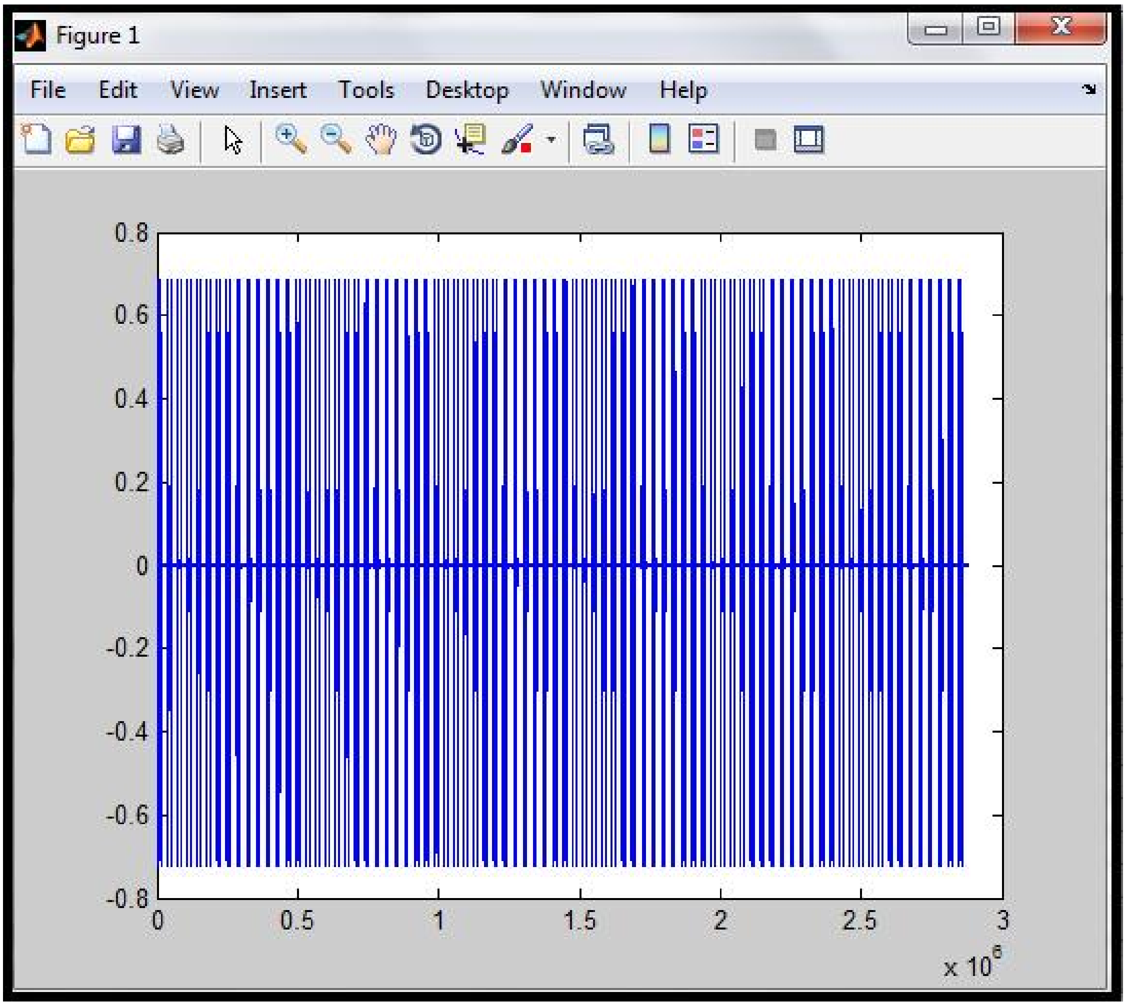


Figure (4.8a): original signal of abnormal heart sounds.

Then Computed DWT-db5 coefficients fifth level shown in Figure (4.9a) for **wavelet decomposition** process.

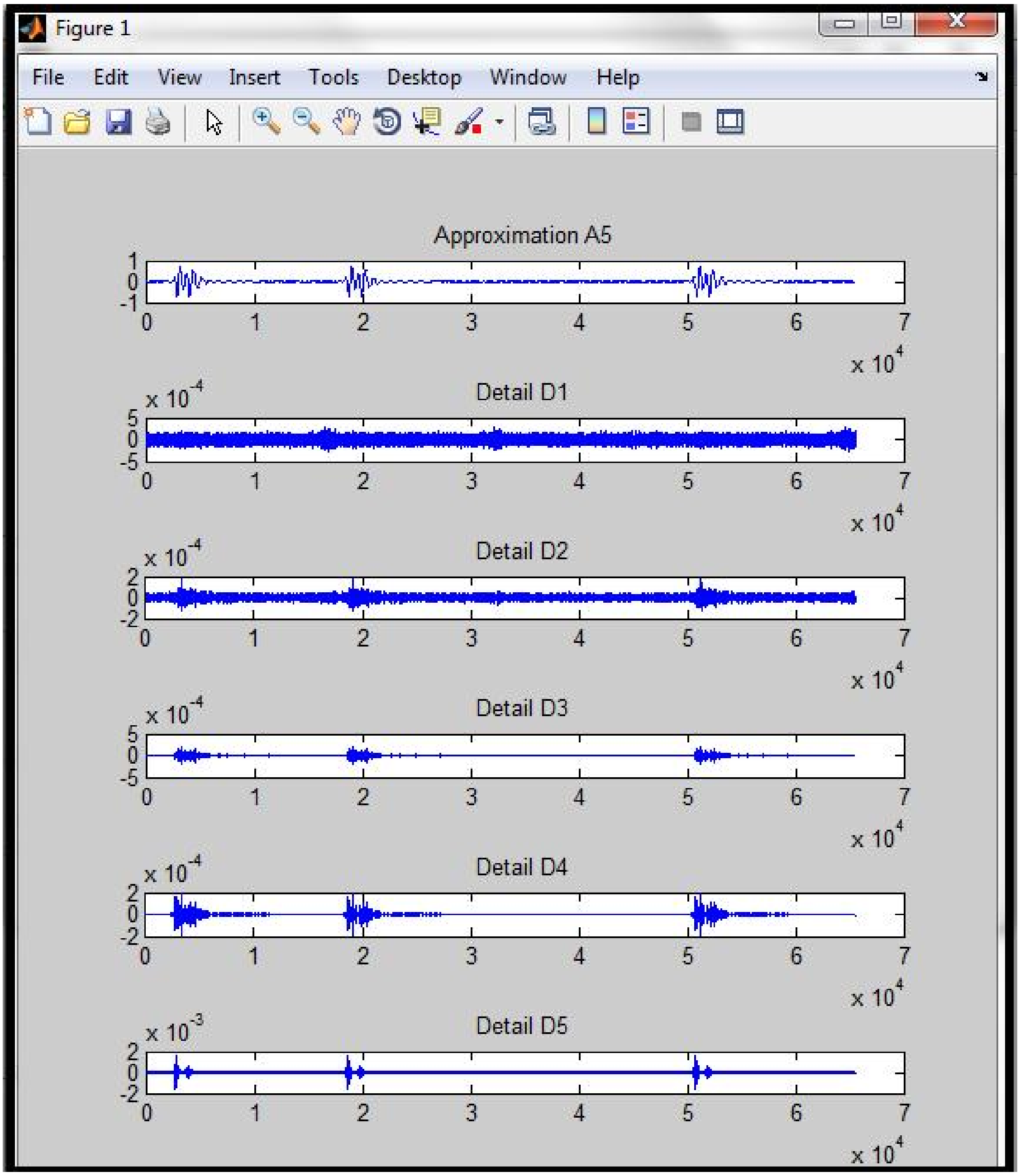


Figure (4.9a): wavelet coefficients using db5.

Wavelet Reconstruction

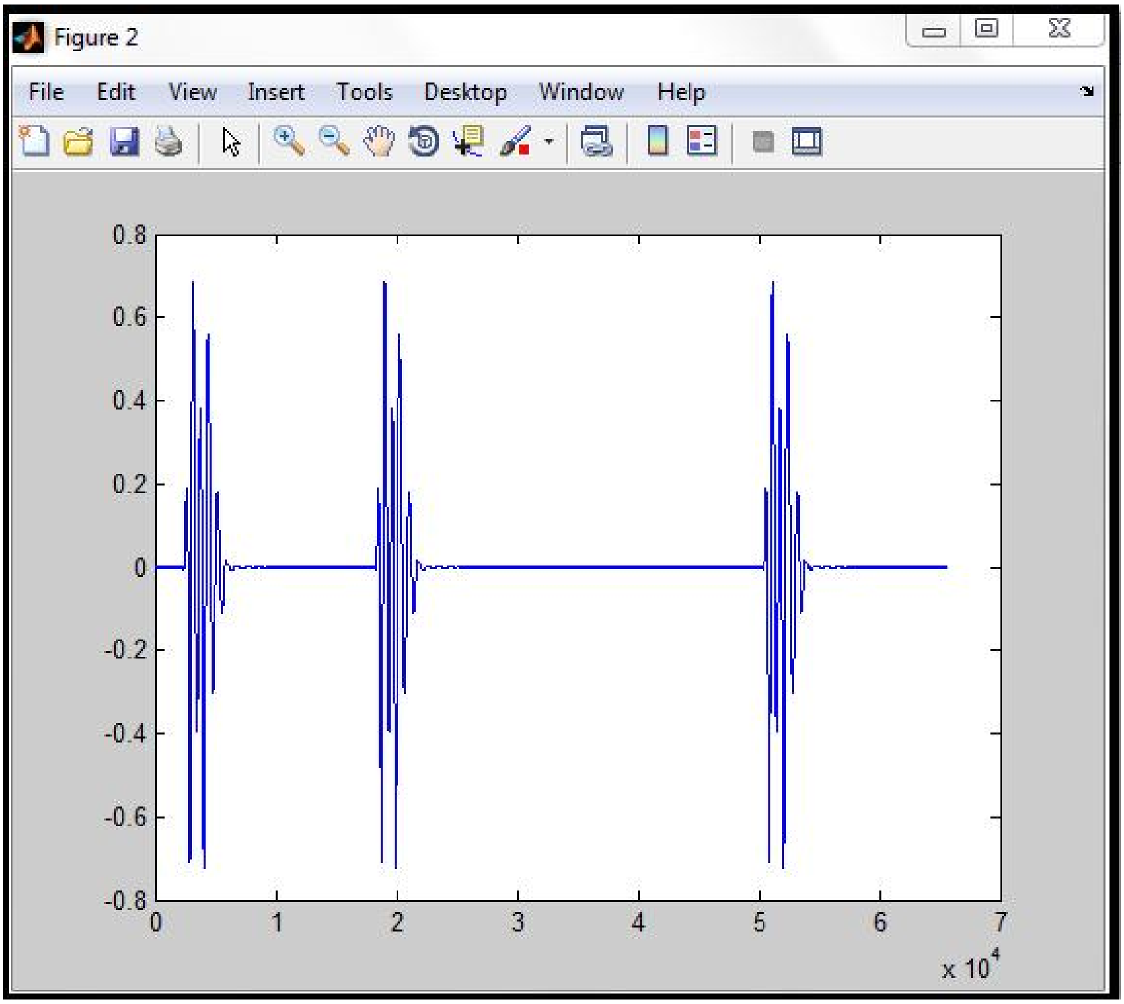


Figure (4.10a): signal from combination wavelet coefficients.

In this figure (IDWT) was applied by combination wavelet coefficients through summation of the original approximation coefficients of the last level (level5) and the modified detail coefficients of levels 2 to 5.

Denoising signal

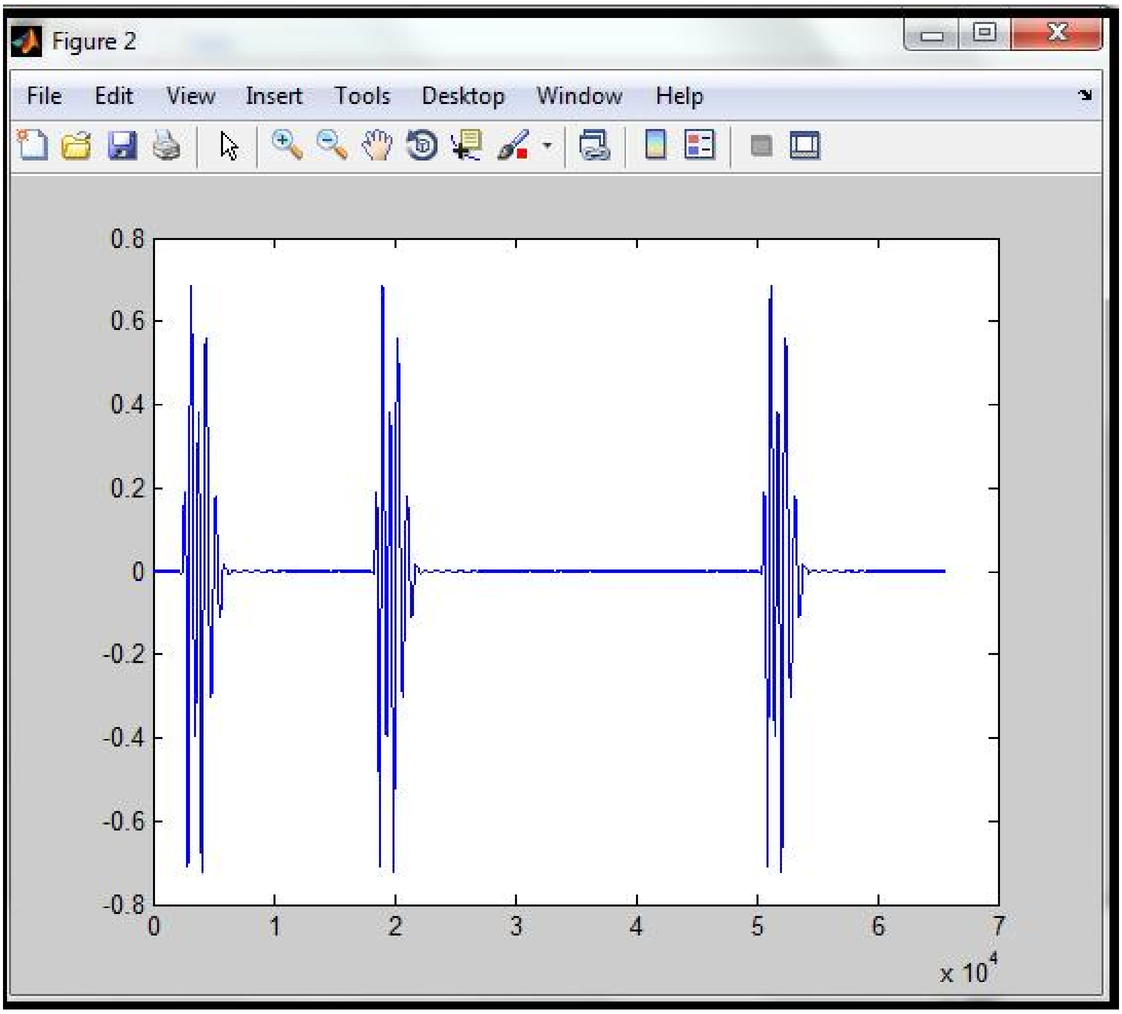


Figure (4.11a): soft threshold de-noising signal.

We note that the highest frequencies appear at the start of the original signal, and the de-noised signal is flat initially. The method chosen here is the soft thresholding, where it produces better result than hard thresholding.

The spectrogram

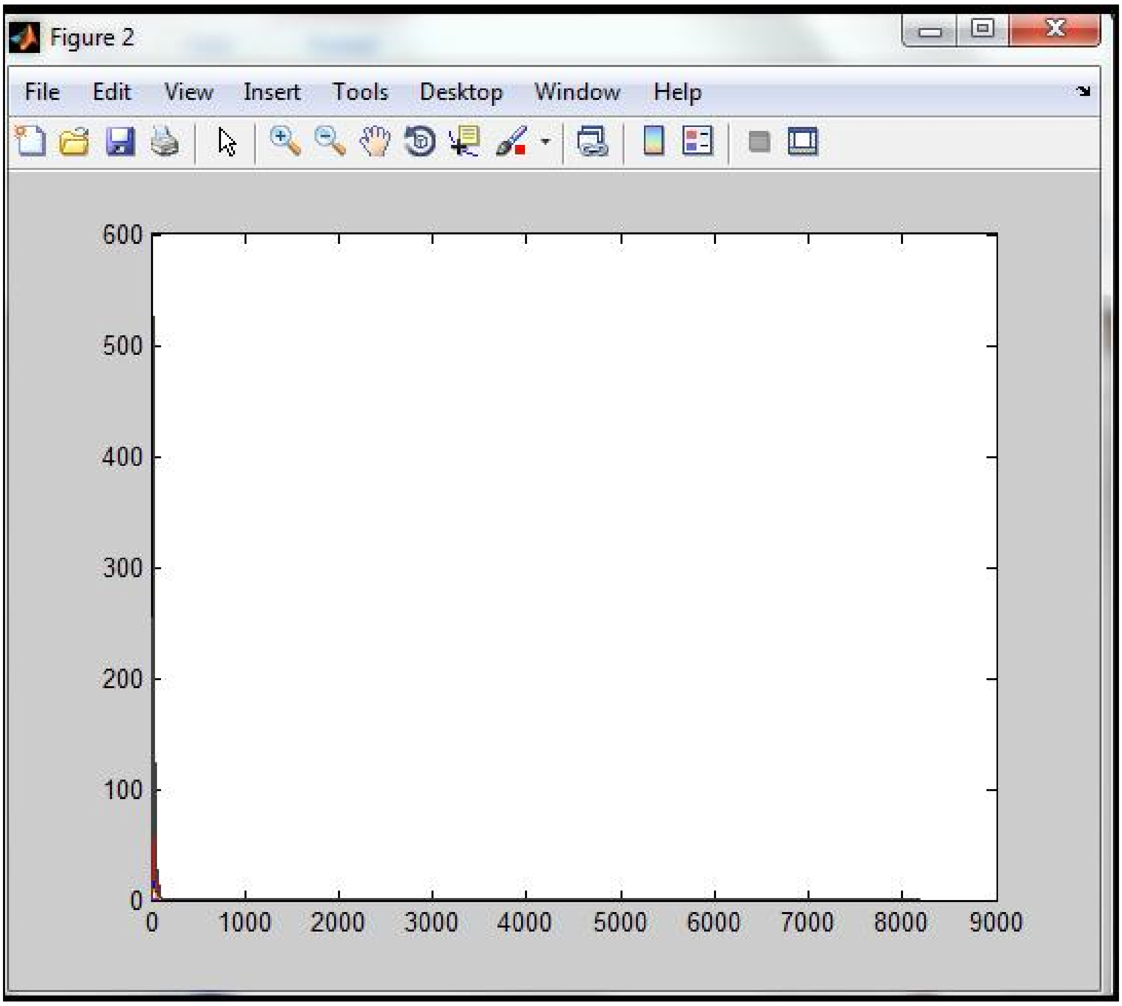


Figure (4.12a): spectrogram of the processed signal.

The Figure shows the time-varying spectral representation that plots the variation of spectral density with respect to time which called spectrogram.

The signal PSD

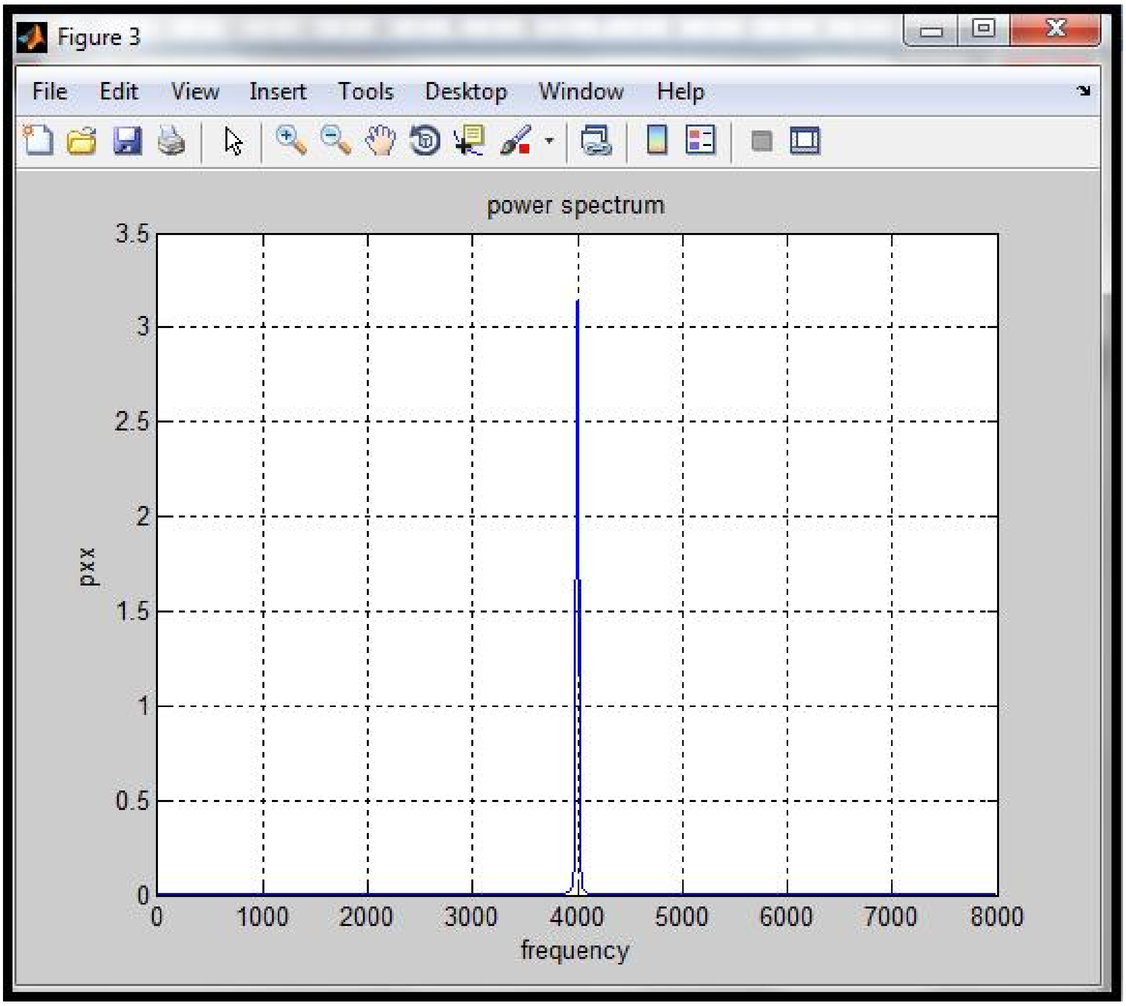


Figure (4.13a): power spectrum of the signal

The peak value of PSD in abnormal case is highest than normal case, where the PSD means measurement of the energy at various frequencies.

Classification process

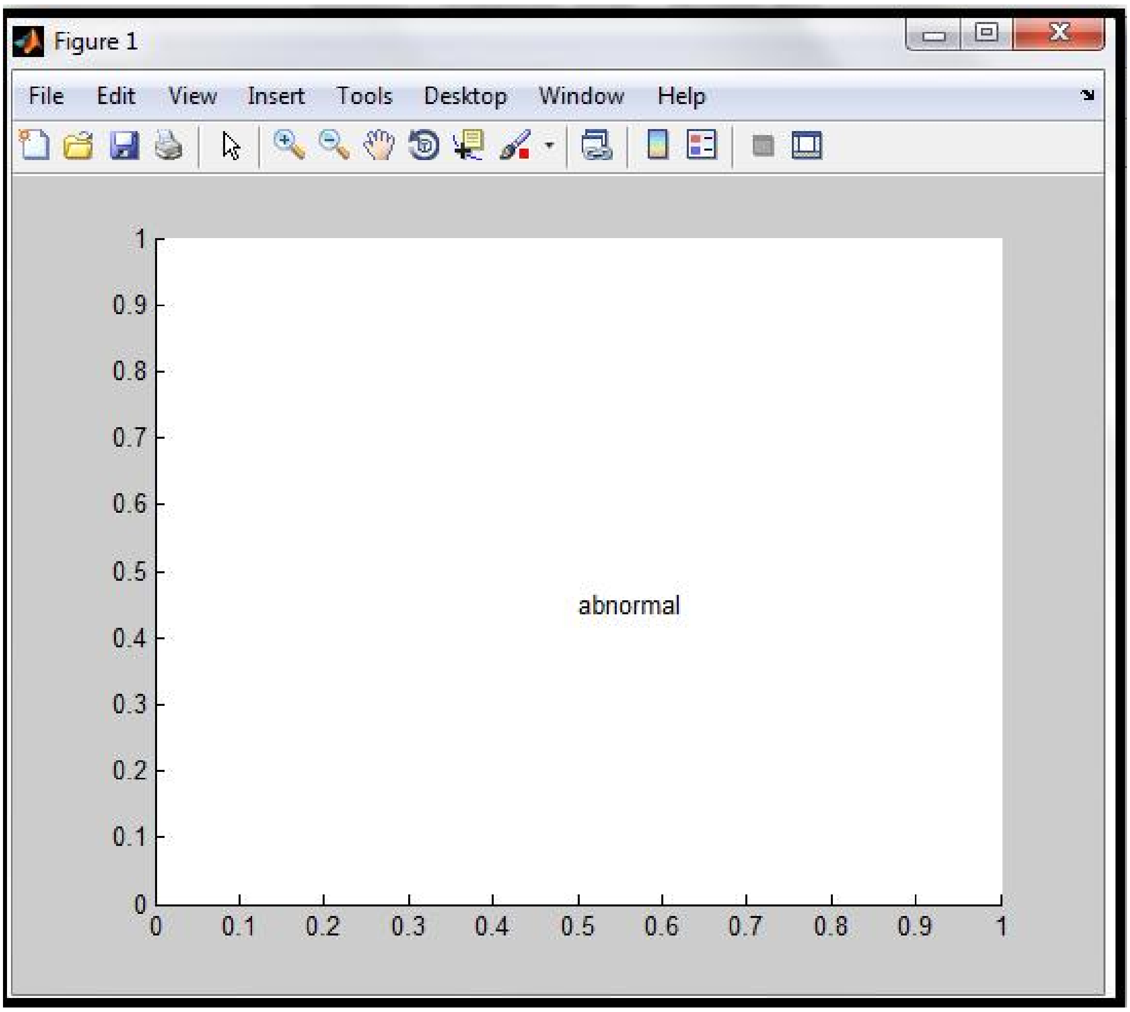


Figure (4.14a): illustrate the classification of the signal.

Due to comparative features the signal classified to abnormal case.

Table [4.1]: Features of Heart Sounds (offline phase)

Number	Signal Name	Kurtosis(K)	Variance(V)	Standard deviation (STD)	Mean(M)	Euclidean distance	Classification process match/mismatch
1	Heart beat_1	40.9437	0.0004	0.0348	0.0173	3.32	matched
2	Heart beat_2	40.9468	0.0004	0.0348	0.0173	3.42	matched
3	Heart beat_3	44.9798	0.0003	0.0321	0.0144	3.50	matched
4	Heart beat_4	37.7655	0.0004	0.0379	0.0158	2.85	matched
5	Heart beat_5	37.7655	0.0004	0.0379	0.0158	2.75	matched
6	Heart beat speeding1	39.1454	0.0000008	0.0009	0.00001	3.10	matched
7	Heart beat speeding2	48.149	0.000008	0.005	0.0003	4.98	matched
8	3hs.wav	37.2948	0.0177	0.0026	0.1303	2.76	matched
9	3hs(1).wav	37.2948	0.0177	0.0026	0.1303	2.76	matched
10	3hs(2).wav	37.2948	0.0177	0.0026	0.1303	2.76	matched
11	4 hs .wav	27.6336	0.0198	0.0027	0.1520	2.53	matched
12	4hs(1).wav	27.6336	0.0198	0.0027	0.1520	2.53	matched
13	4hs(2).wav	27.6336	0.0198	0.0027	0.1520	2.53	matched
14	atrial fibrillation.wav	12.9443	0.0067	0.1502	0.0459	2.15	matched
15	aortic regurgitation.wav	11.8347	0.0127	0.0922	0.0606	2.37	matched
16	aortic stenosis.wav	10.1013	0.1276	0.0236	0.0119	3.10	matched

17	sumg.wav	26.7633	0.0169	0.0025	0.1316	3.00	matched
18	mitral regurgitation	14.4113	0.0565	0.0152	0.0088	2.77	matched
19	mitral stenosis.wav	20.6265	0.0180	0.0025	0.0011	2.85	matched
20	pericardial friction	44.7541	0.0017	0.0795	0.0505	2.15	matched
21	summation gallop2.wav	24.44	0.0118	0.1075	0.0293	0.22	mismatched
22	summation gallop1.wav	21.38	0.0113	0.1067	0.0288	0.18	mismatched
23	normal.wav	24.74	0.0118	0.1085	0.0298	0	matched
24	normal(1).wav	23.84	0.0117	0.1075	0.0297	0.02	matched
25	normal(2).wav	22.70	0.0115	0.1069	0.0295	0.09	matched
26	normal(3).wav	20.71	0.0112	0.1063	0.0288	0.13	matched
27	normal(4).wav	21.64	0.0113	0.1067	0.0290	0.10	matched
28	normal(5).wav	24.74	0.0118	0.1085	0.0298	0	matched
29	normal(6).wav	24.74	0.0118	0.1085	0.0298	0	matched
30	Normal new web	21.3050	0.0024	0.0456	0.0158	2.30	mismatched

From Table [4.1] the results features of normal cases at index number (23, 28, and 29) were selected as control signal features in order to accomplish classification process. As well as if (Kurtosis<=24074 and Mean<=0.0298, and Variance<=0.0118 and STD<= 0.1085 and EUC<=2) then classified to normal case else classified to abnormal case.

4.1.3 Verification result for offline data

4.1.3.1 Predictive values

Now to verify result of offline data, calculate the true positive value (TP), false positive value (FP), true negative value (TN), and false positive value (FN) from algorithm results which applied in offline data to calculate sensitivity, specificity and accuracy of the system.

Table [4.2]: Predictive values (TP, TN, FP and FN) of the system

statement	normal	abnormal	Total
Positive	07 (True Positive)	20 (True Negative)	27 $T_{\text{Test Positive}}$
Negative	01 (False Positive)	02 (False Negative)	03 $T_{\text{Test Negative}}$
	08 T_{normal}	22 T_{abnormal}	30 Total

$$\text{Prevalence of normal} = \text{Total}_{\text{normal}} \setminus \text{Total} * 100 \tag{1a}$$

$$\text{Prevalence of normal cases} = 08 \setminus 30 * 100 = \underline{\underline{26.66\%}}$$

4.1.3.2 Accuracy and sensitivity of the system algorithm:

Sensitivity is the probability that algorithm was classify 'normal' among those with the normal cases:

$$\text{Sensitivity} = TP/\,(TP+FP) \times 100 \tag{2a}$$

Sensitivity = $7/(7+1) \times 100 = \underline{\underline{87.5\%}}$

Specificity is the fraction of those abnormal cases, which have a negative algorithm result:

$$\text{Specificity} = FN / (FN + TN) \times 100 \qquad (3a)$$

∴ Specificity = 02/(02+20) × 100 = 9.09 %

Accuracy:

Accuracy is how close a measured value is to the actual (true) value.

$$\boxed{\text{Accuracy} = \frac{\text{Number of correct samples}}{\text{Number of all samples}} * 100\%} \qquad (4a)$$

Accuracy= 27/30 *100 =90%

4.2 RESULT B: (REAL TIME DATA)

The heart sounds were collected from Sudan Heart Center and Best-Care Hospital; the recordings were made using the implemented Electronic Stethoscope for about 10 seconds each. A total of 30 volunteers aged from 18 to 75 years with 17 normal case and 13 various pathologies cases were used in this current study. Heart sounds for abnormal cases were recorded with assistance from the patients. In preprocessing stage, an adaptive filter was used to filter heart sounds from lung sounds, due to lung sound overlapped with heart sound in sub frequency band. Then, the background noise was minimized using wavelet transform (db5, level5). At the feature extraction stage graphical and statistics features vector elements are formed for both time and frequency domain. Finally, classification process was accomplished by look-up table. The implementation of the proposed algorithm produced accuracy of 80%, and sensitivity of 82.4%.

4.2.1 Simulation result of an electronic stethoscope circuit

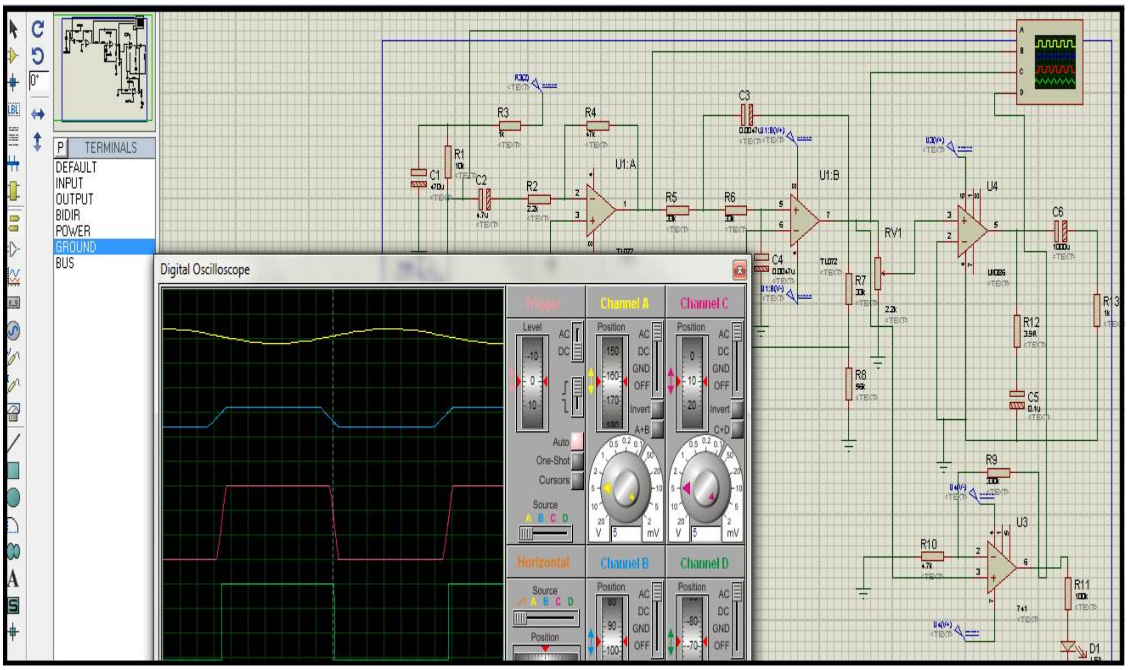


Figure (4.1b): illustrates the simulation result of integrated circuit.

- U1a operates as a low-noise microphone preamplifier. Its gain is only about 3.9.
- U1b operates as a low-noise reduction, Butterworth 2nd order low pass filter with gain of 1.6 and cutoff frequency of about 103Hz.
- The U3 circuit is optional and has a gain of 71 to drive the bi-color LED.
- U4 is a 1/4W power amplifier IC (LM386) with gain of 20. It can drive any type of headphones including low impedance (8 ohms) ones.

4.2.2 Original normal signal recorded by an electronic stethoscope

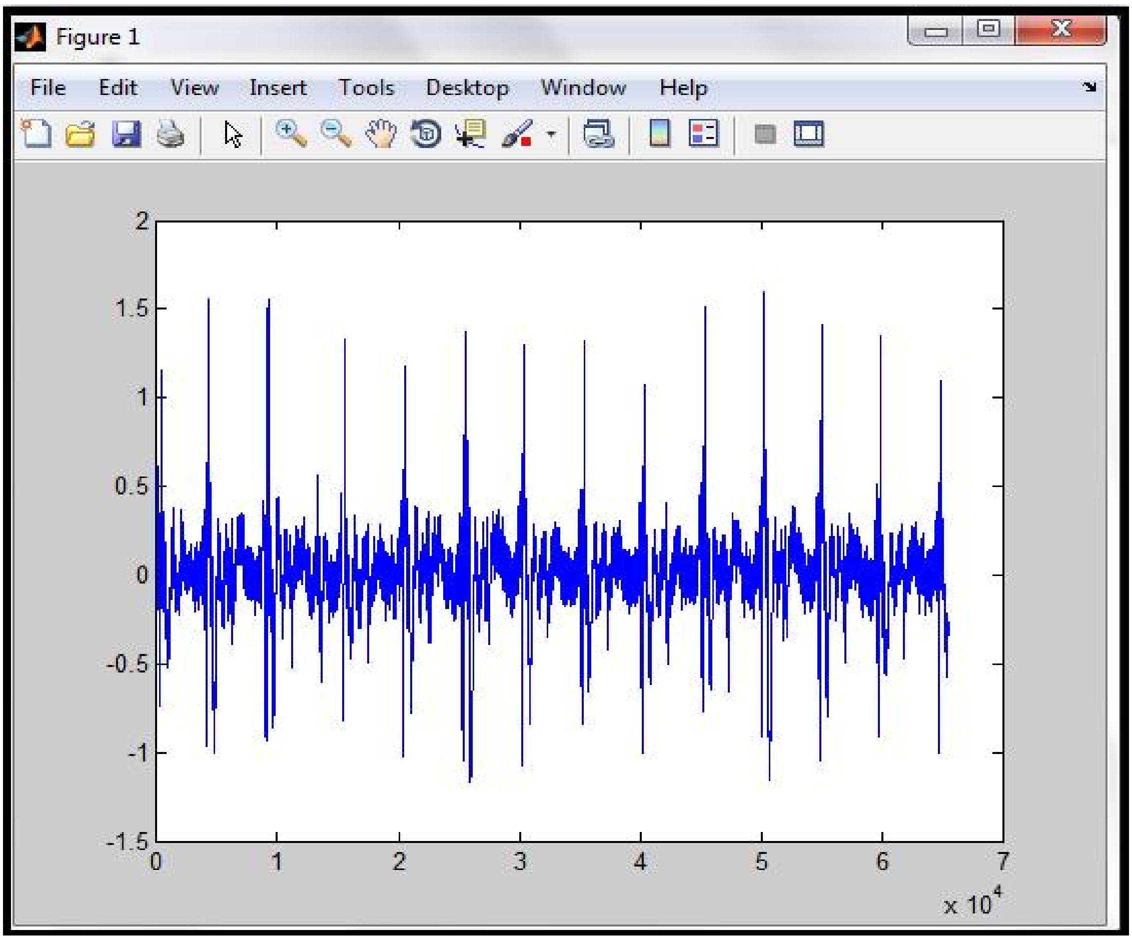


Figure (4.2b): original signal of normal case recorded in real time

Adaptive filter for cancelation lung sound from heart sound

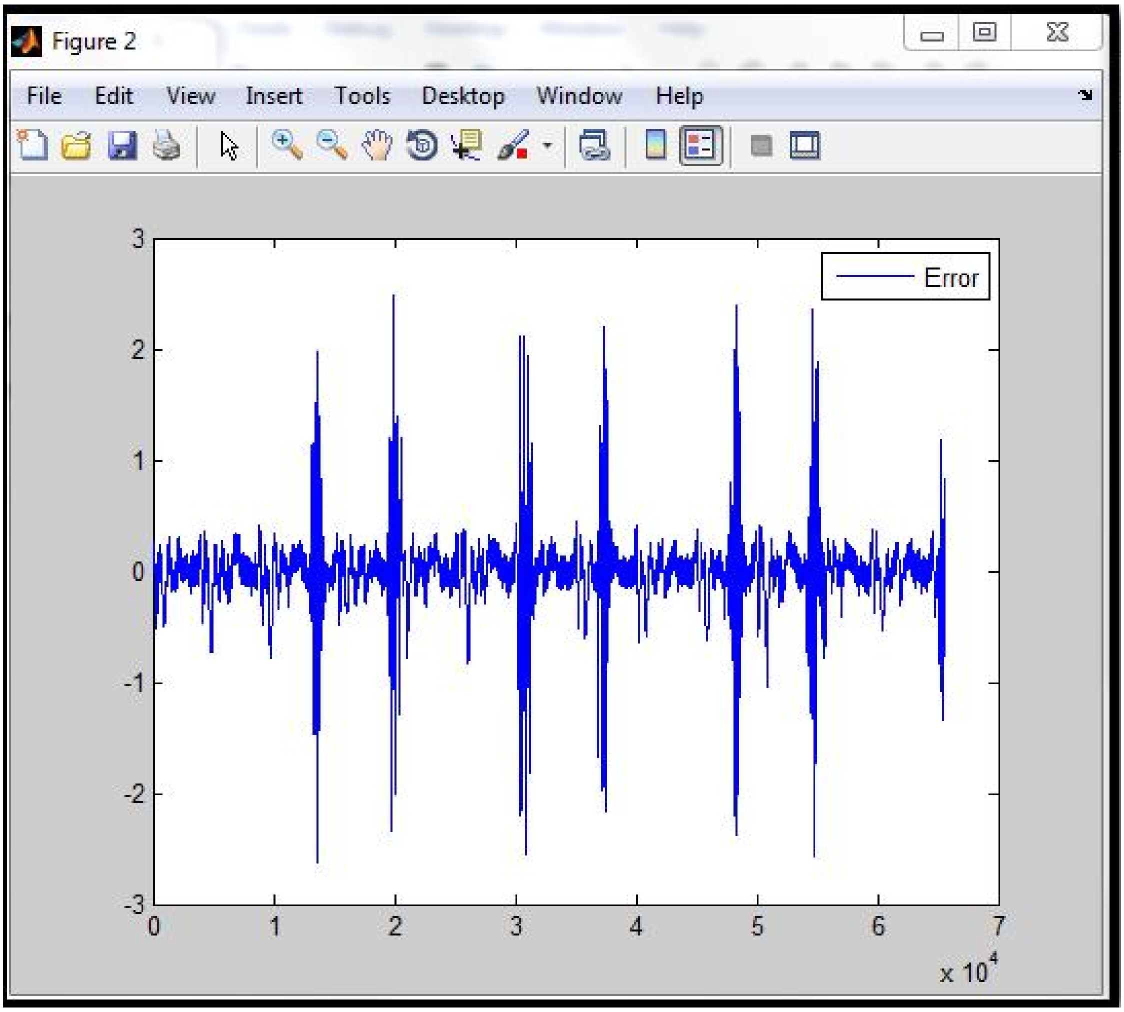


Figure (4.3b): adaptive filter process for normal recorded case.

Due to features of heart sounds impure by lung sounds, because the lung and the heart sound overlap in terms of time domain and spectral content. Then the Adaptive filter was applied for cancelation Lung sound from original normal recorded signal**.**

Wavelet transform to minimize background noise

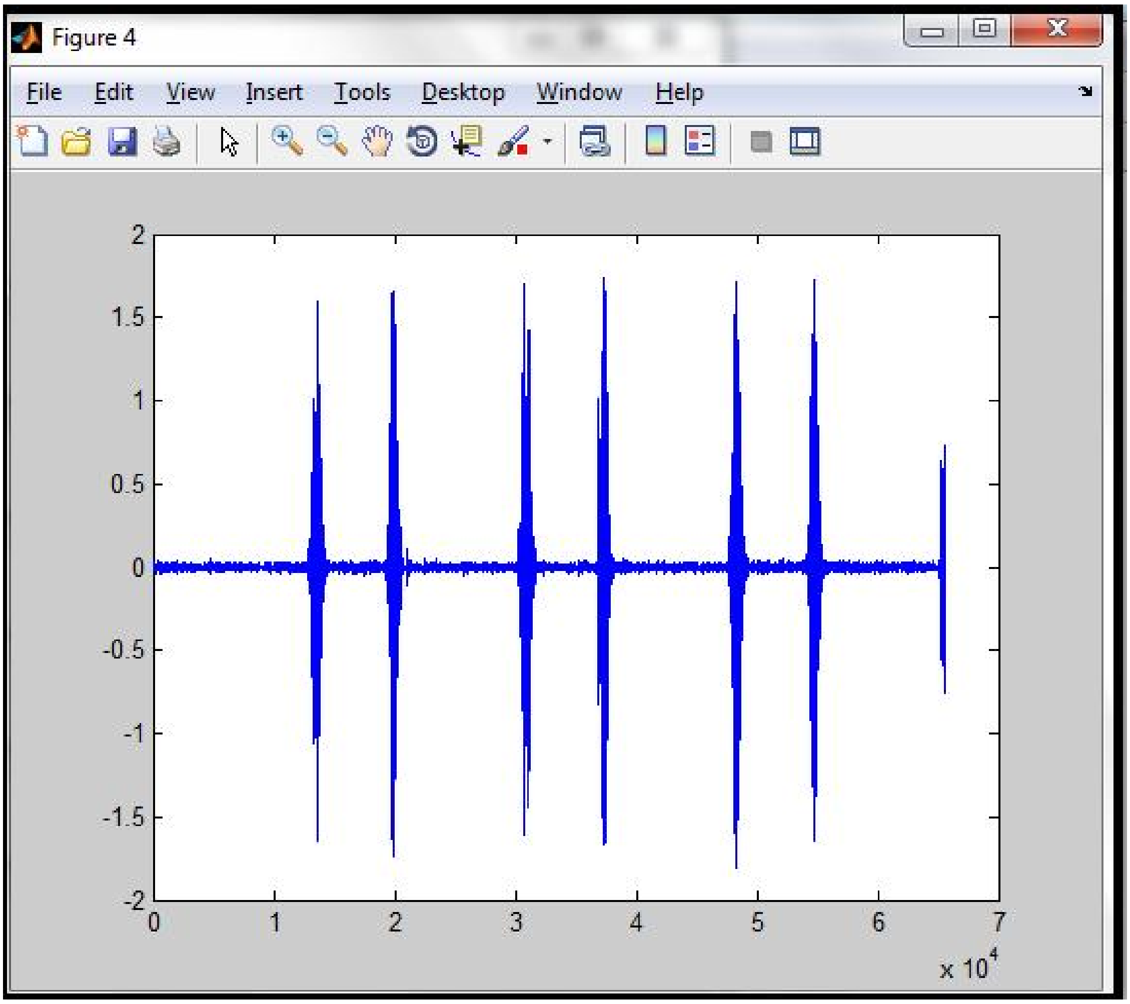


Figure (4.4b): minimized background noise using DWT for normal case.

Wavelet applied for purred normal signal to minimize background noise such as muscle contraction blood flow and patient movement by applying DWT (db5, level5) which decomposed signal into approximation and details, then IDWT was applied to reconstruct signal by summing details and A5.

Denoising signal

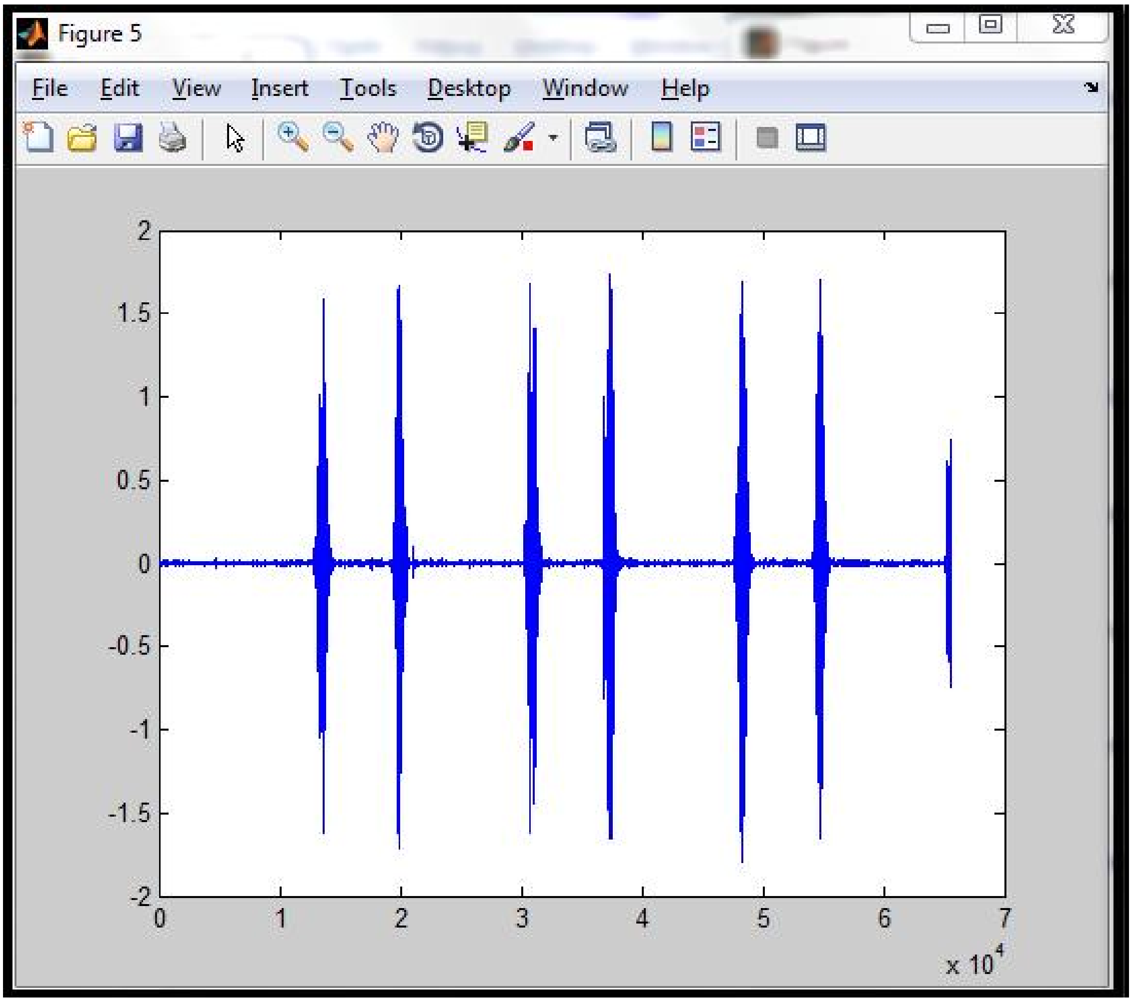


Figure (4.5b): soft threshold de-noising for normal case.

The Soft threshold was selected to denoising the purred normal signal.

Then the Spectrogram for purred normal signal illustrated as figure (4.6b).

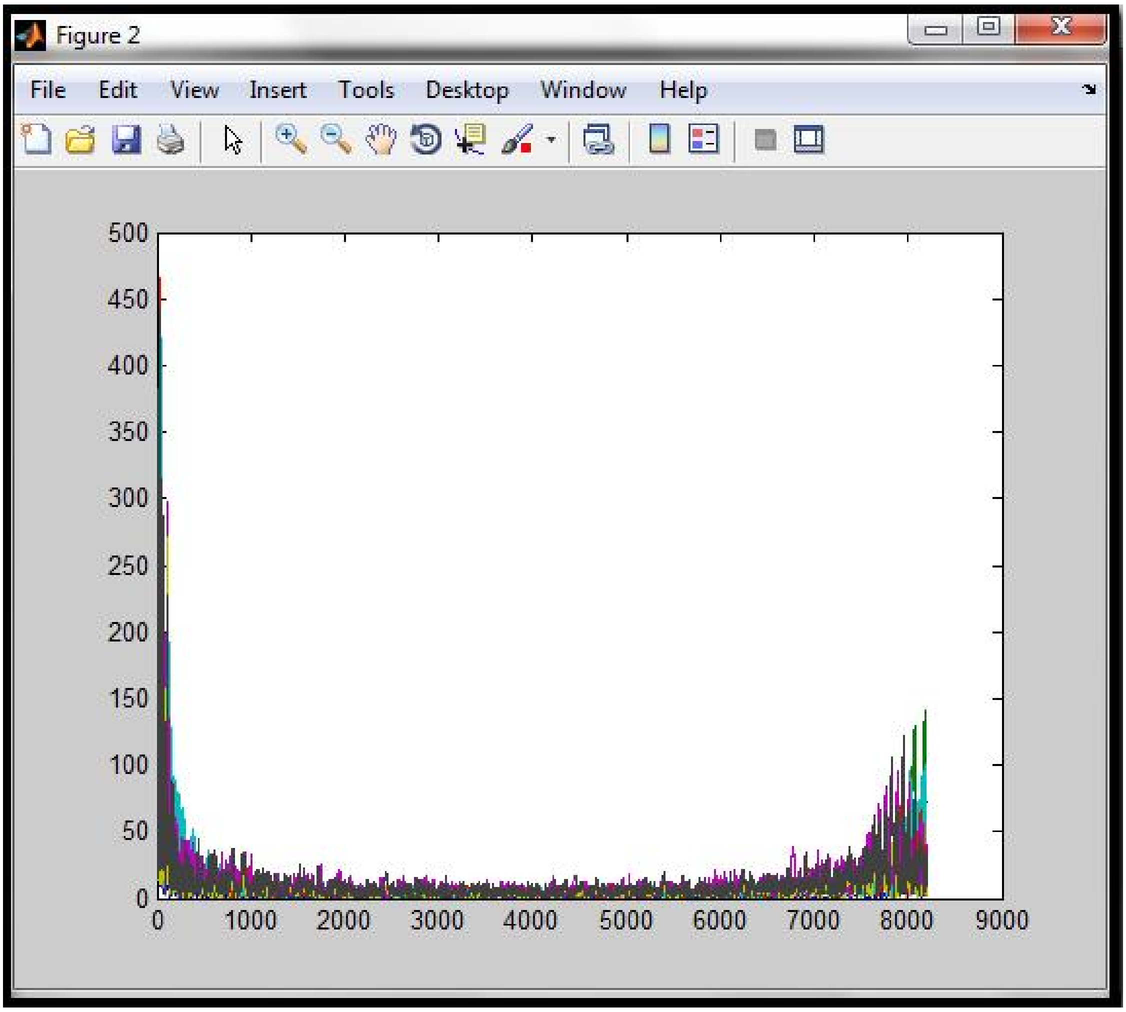


Figure (4.6b): spectrogram of the processed recorded normal case.

Spectrogram is a time-varying spectral representation that plots the variation of spectral density with respect to time. Spectrogram is a two dimensional graph, where horizontal axis represents time and vertical axis represents frequency. A third dimension indicating amplitude of a particular frequency is represented by the intensity or color of each point in the signal.

It has been observed the signal which recorded in real time, has highest intensity than offline data due to variation in power spectrum density.

PSD for purred normal signal was extracted as figure (4.7a).

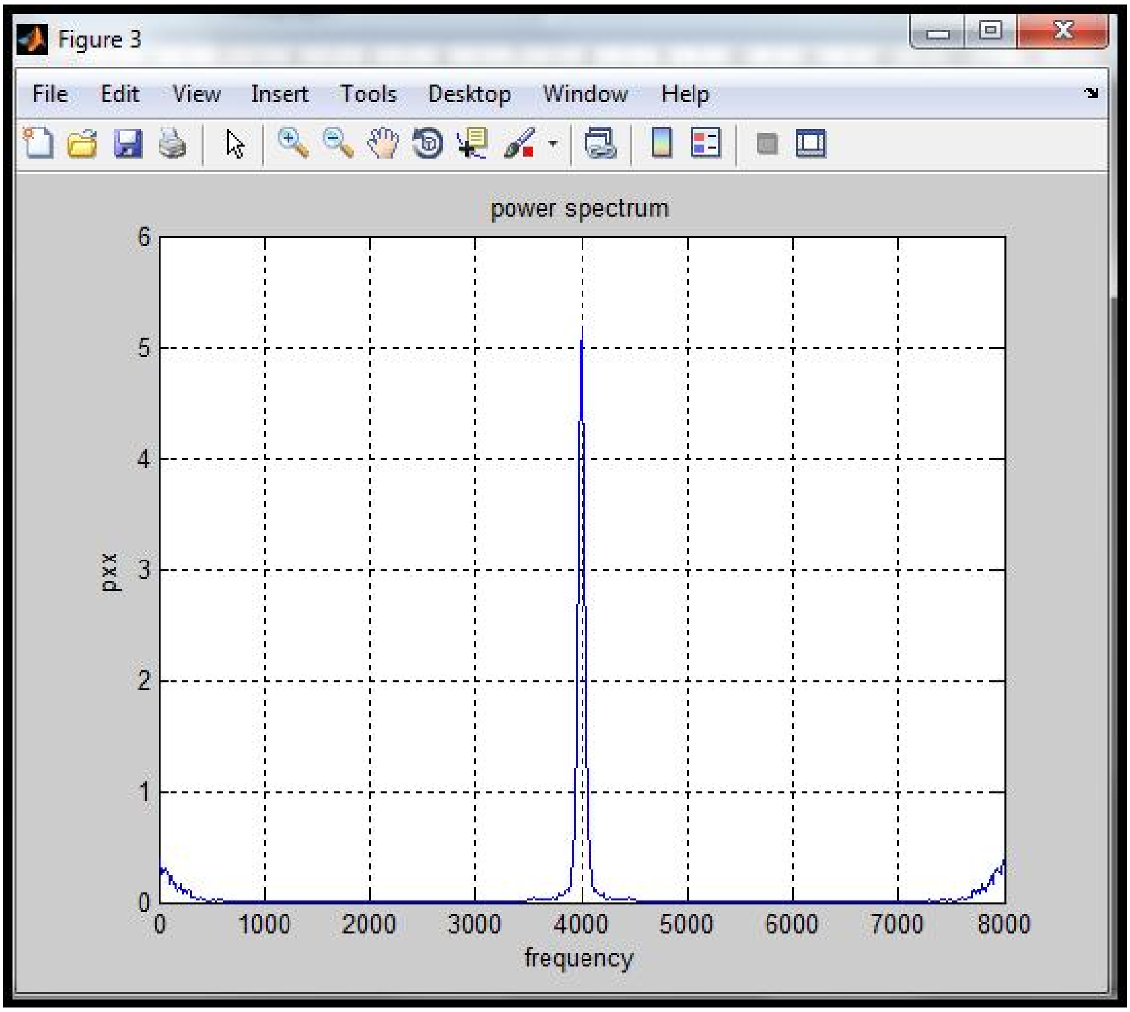


Figure (4.7b): power spectrum of normal recorded case.

It also observed, the peak value of PSD in normal recorded case is highest than abnormal recorded case, where the PSD means measurement of the energy at the various frequencies.

Classification process

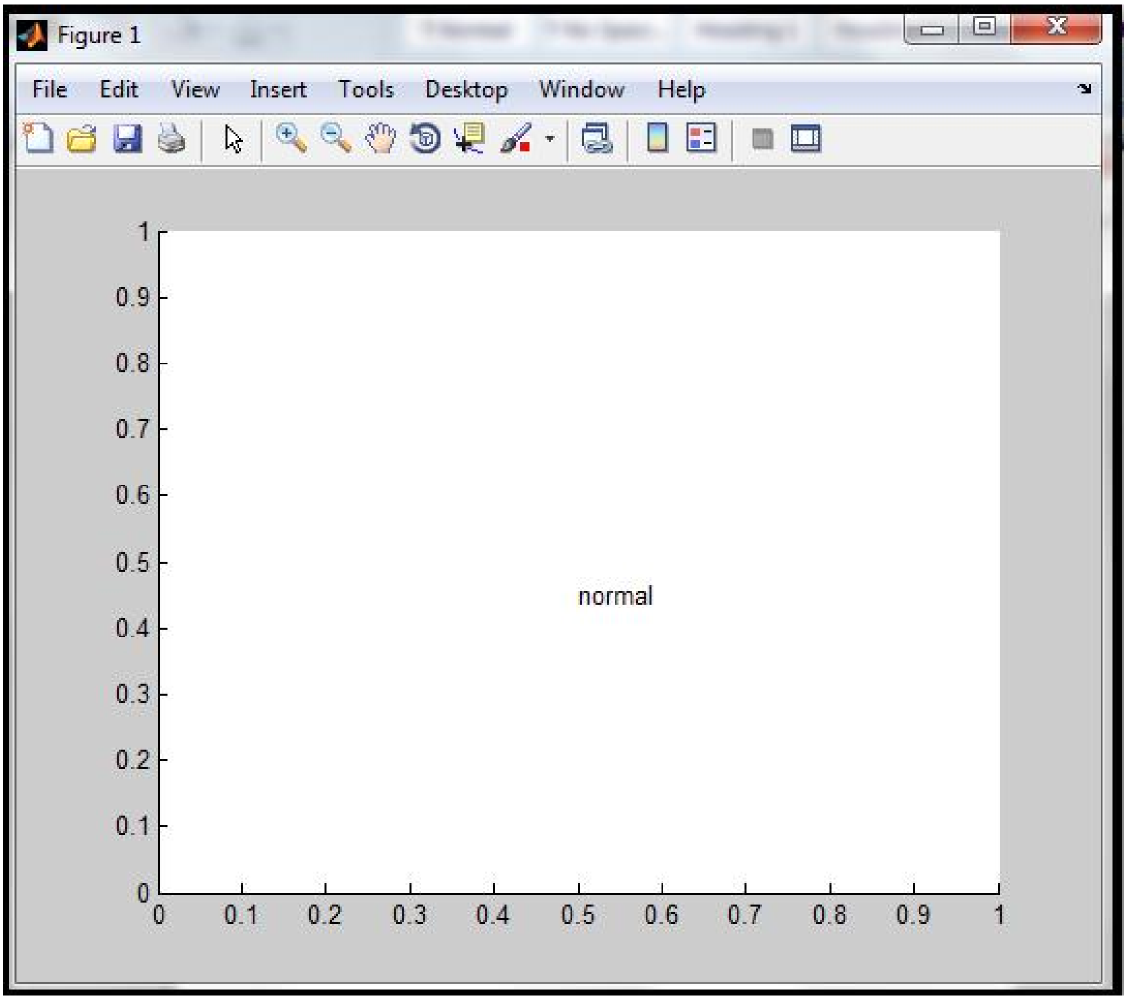


Figure (4.8b): illustrates the classification of normal recorded case.

The classification process was accomplished by comparing the features of sample signal with threshold and features that stored in database (control signal) and then signal was classify as illustrated in figure above.

4.2.3 Original abnormal case (murmur) recorded by an electronic stethoscope

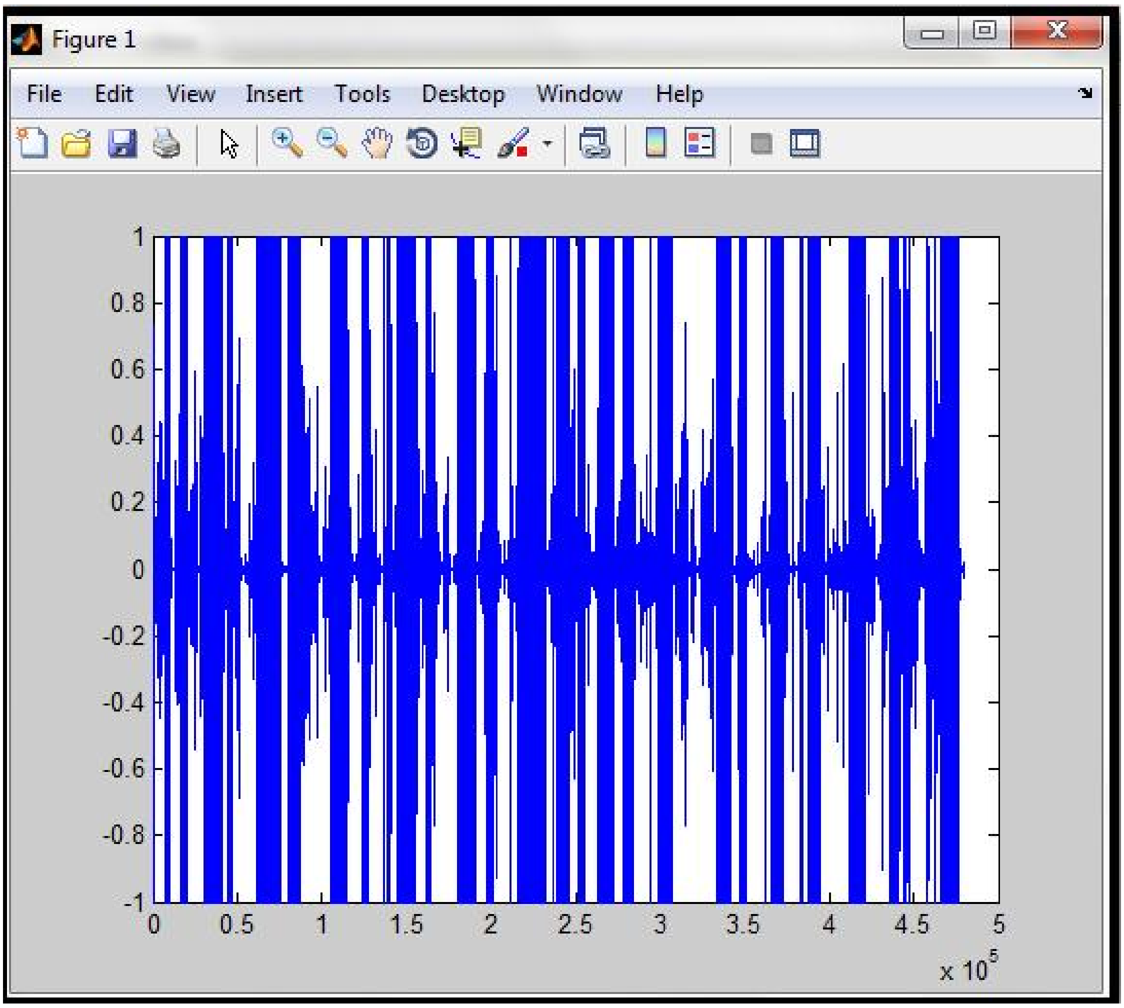
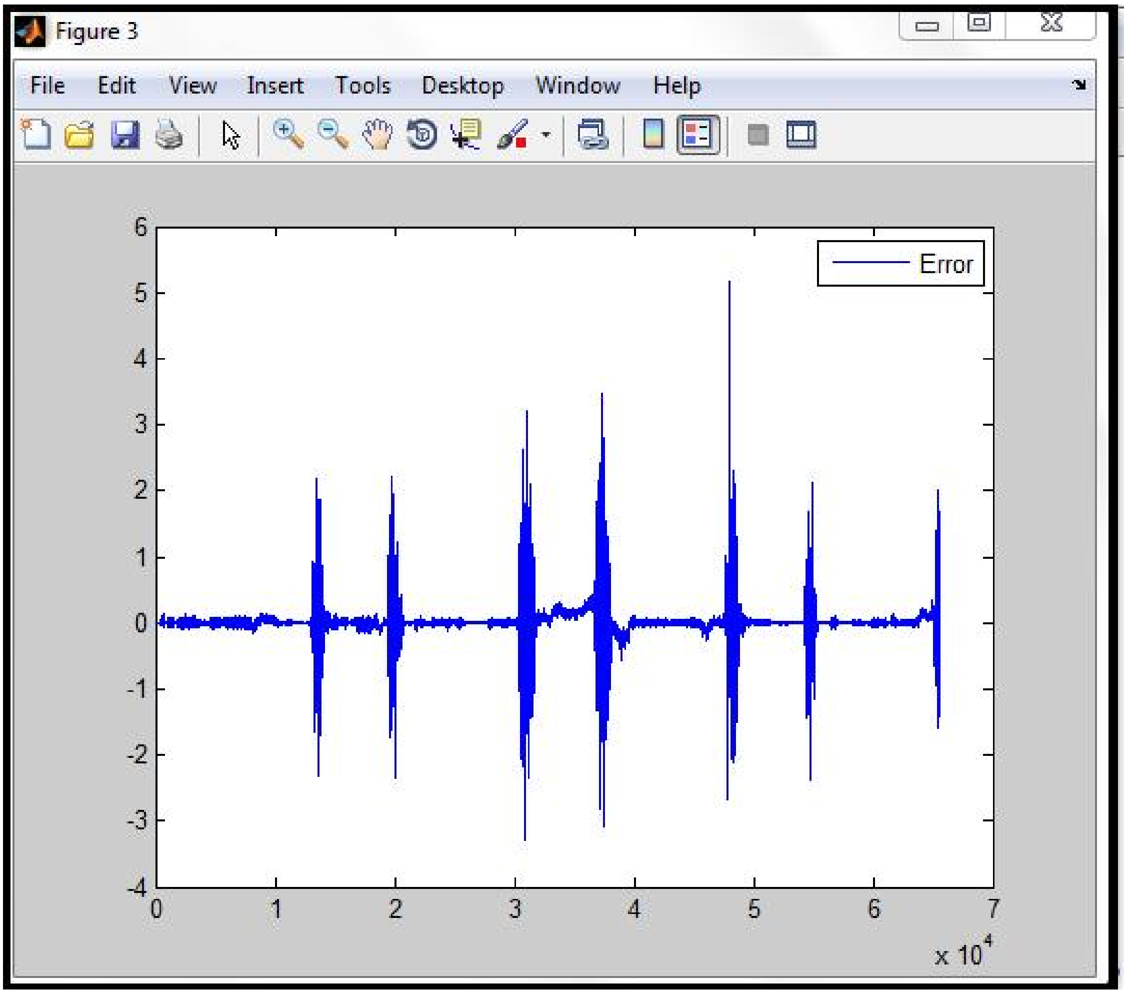


Figure (4.9b): original signal of abnormal case in real time

Adaptive filter for removing lung sound from heart sound



Figure(4.10b): adaptive filter for lung sound cancelation from abnormal case

An adaptive filter was applied to remove lung sound from original abnormal signal due to lung sound overlap with heart sound in sub frequency band.

Wavelet transform to minimize background noise

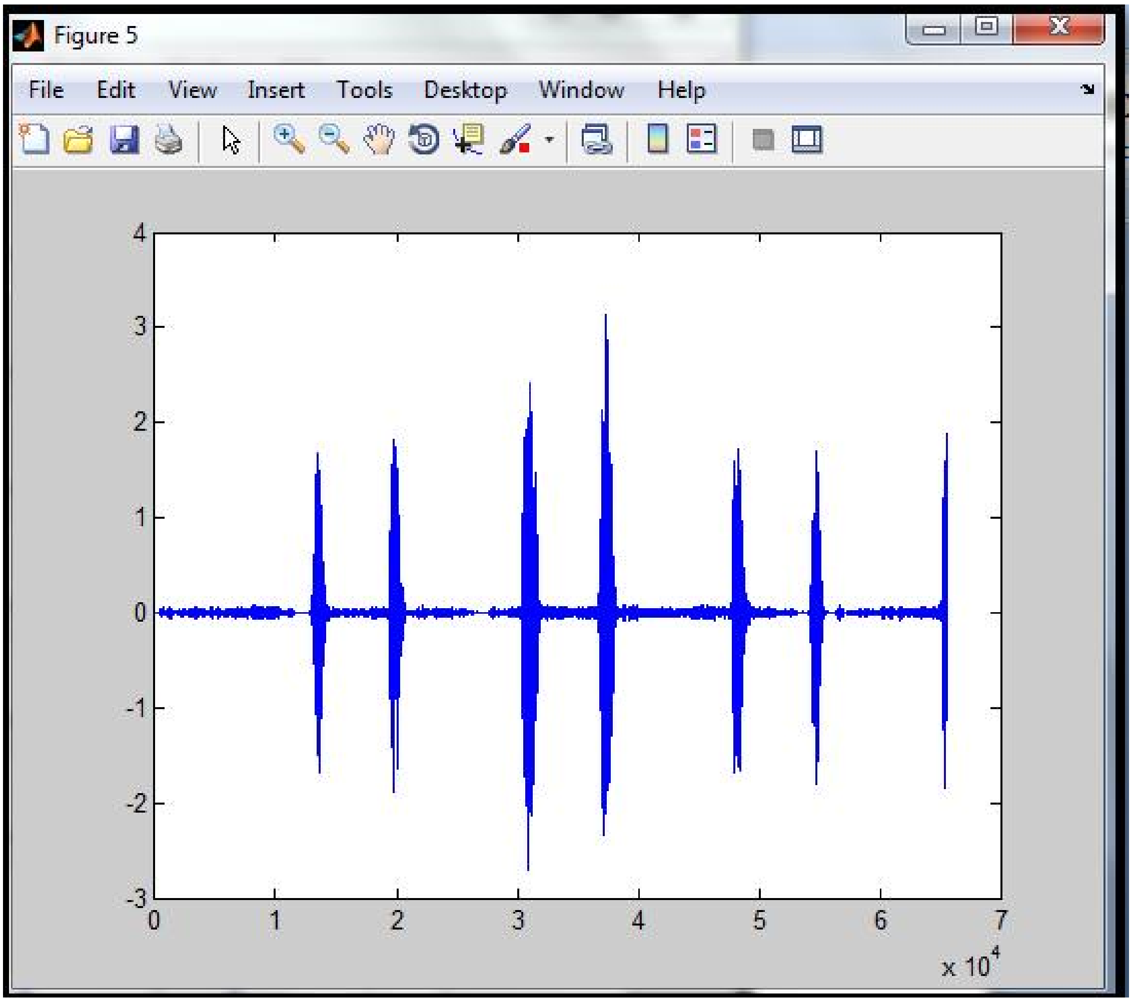


Figure (4.11b): minimized background noise using DWT for abnormal case.

Then wavelet applied for purred abnormal signal to minimize background noise (db5, level5) for decomposition process, and then IDWT applied to reconstruct signal by summing the details with approximation level5.

For denoising signal

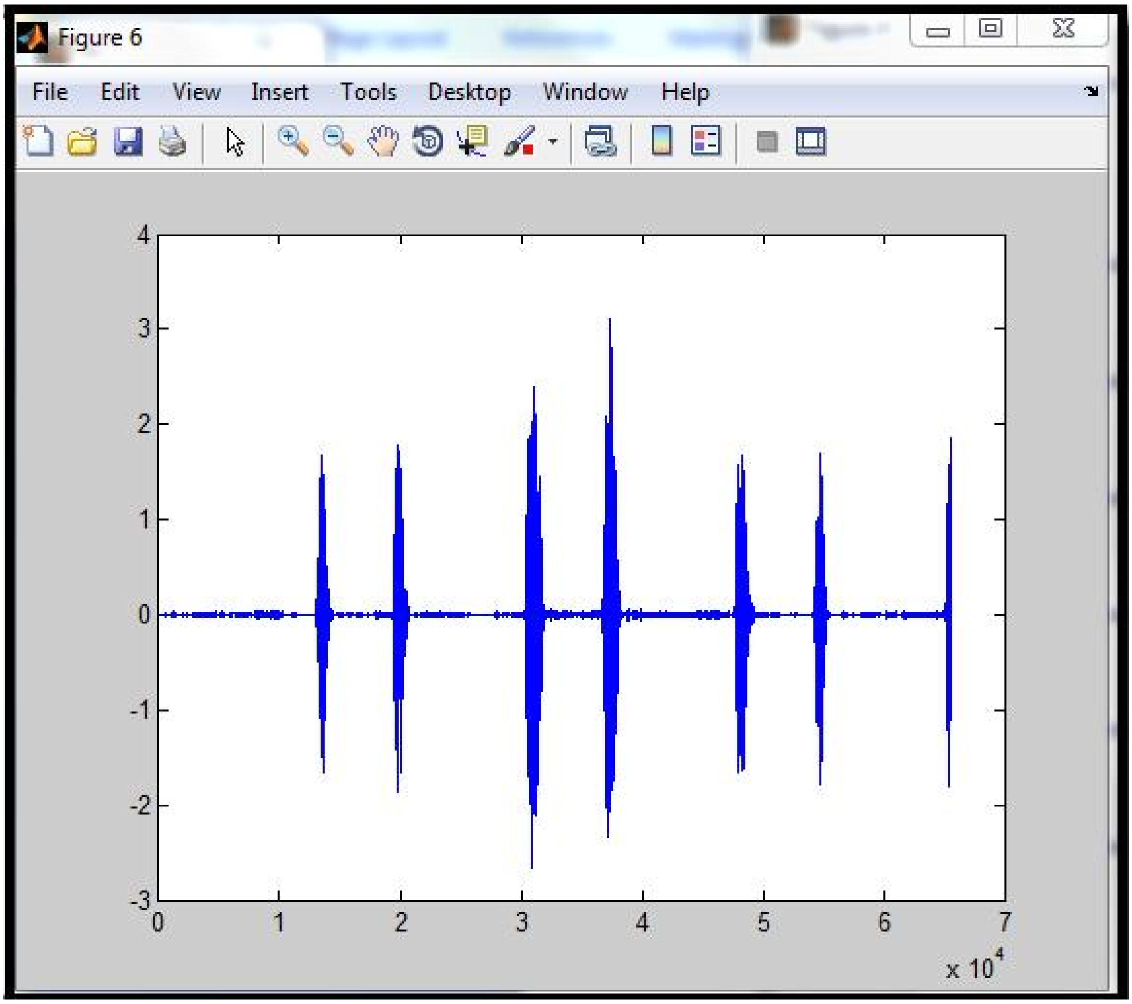


Figure (4.12b): soft threshold de-noising abnormal signal

Soft threshold was selected for de-noising purred abnormal signal, where it produces better result than hard thresholding because it sets the elements whose absolute values are lower than the threshold to zero and then the nonzero coefficients remaining are shrunk and set to zero.

The Spectrogram for purred abnormal signal was illustrated in figure bellow.

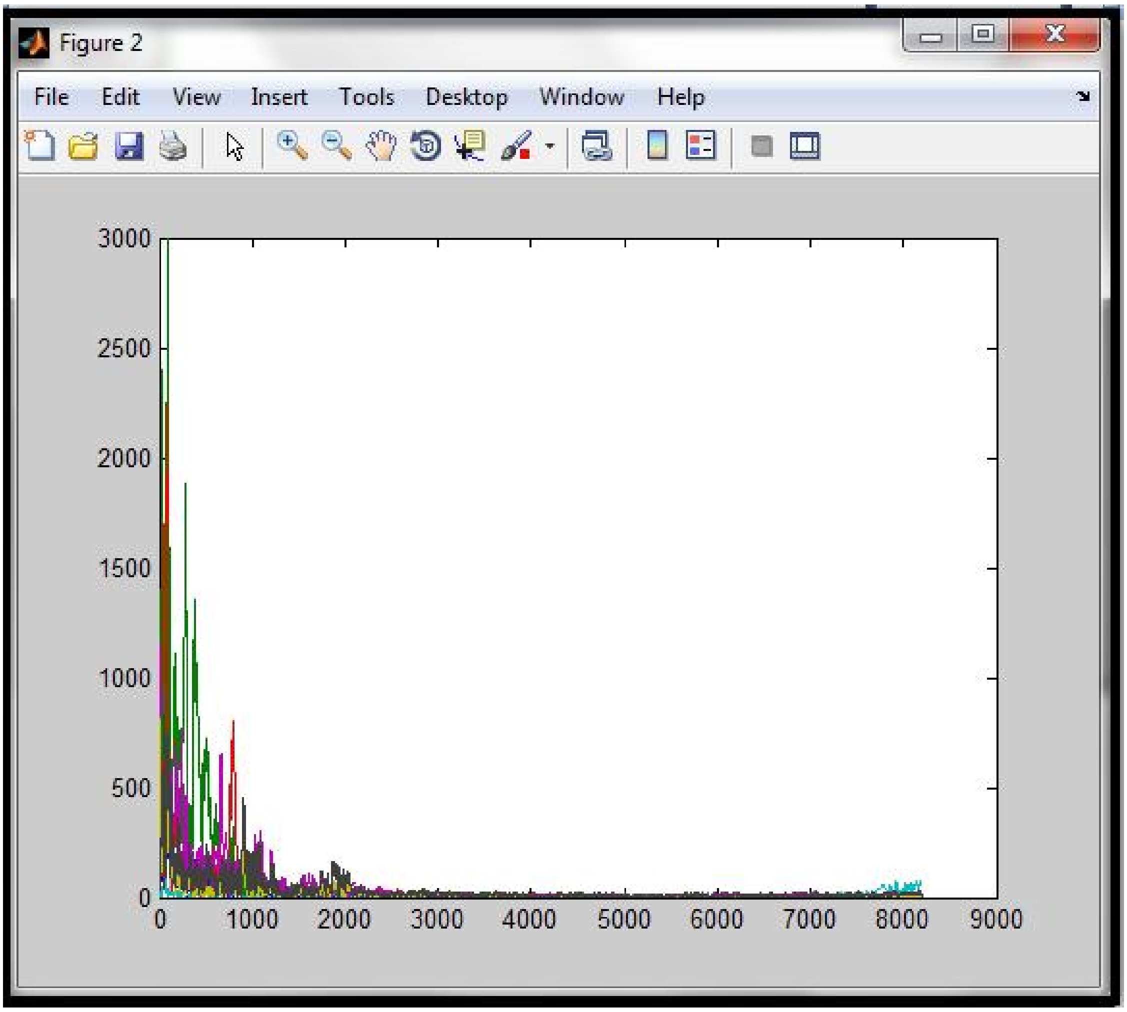


Figure (4.13b): spectrogram of the processed abnormal signal.

Spectrogram is a time-varying spectral representation that plots the variation of spectral density with respect to time, also here is highest than offline abnormal case due to variation in power spectrum density (PSD).

PSD of purred abnormal case

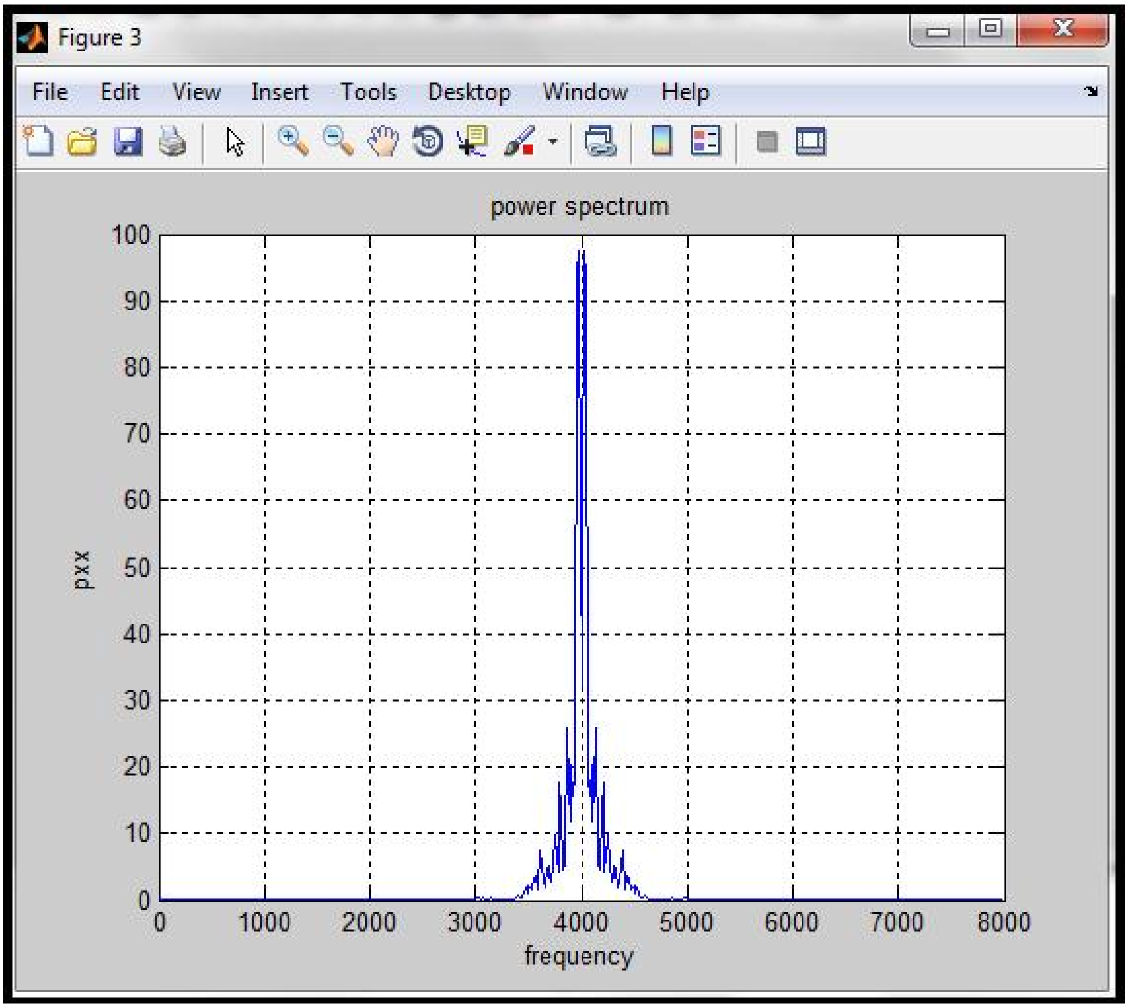


Figure (4.14b): power spectrum of abnormal signal.

The measurement of energy at the various frequencies, which called Power spectrum density, was extracted for purred abnormal signal in above figure. The highest peak value of PSD means the Euclidean distance is greater than 100.

Classification process

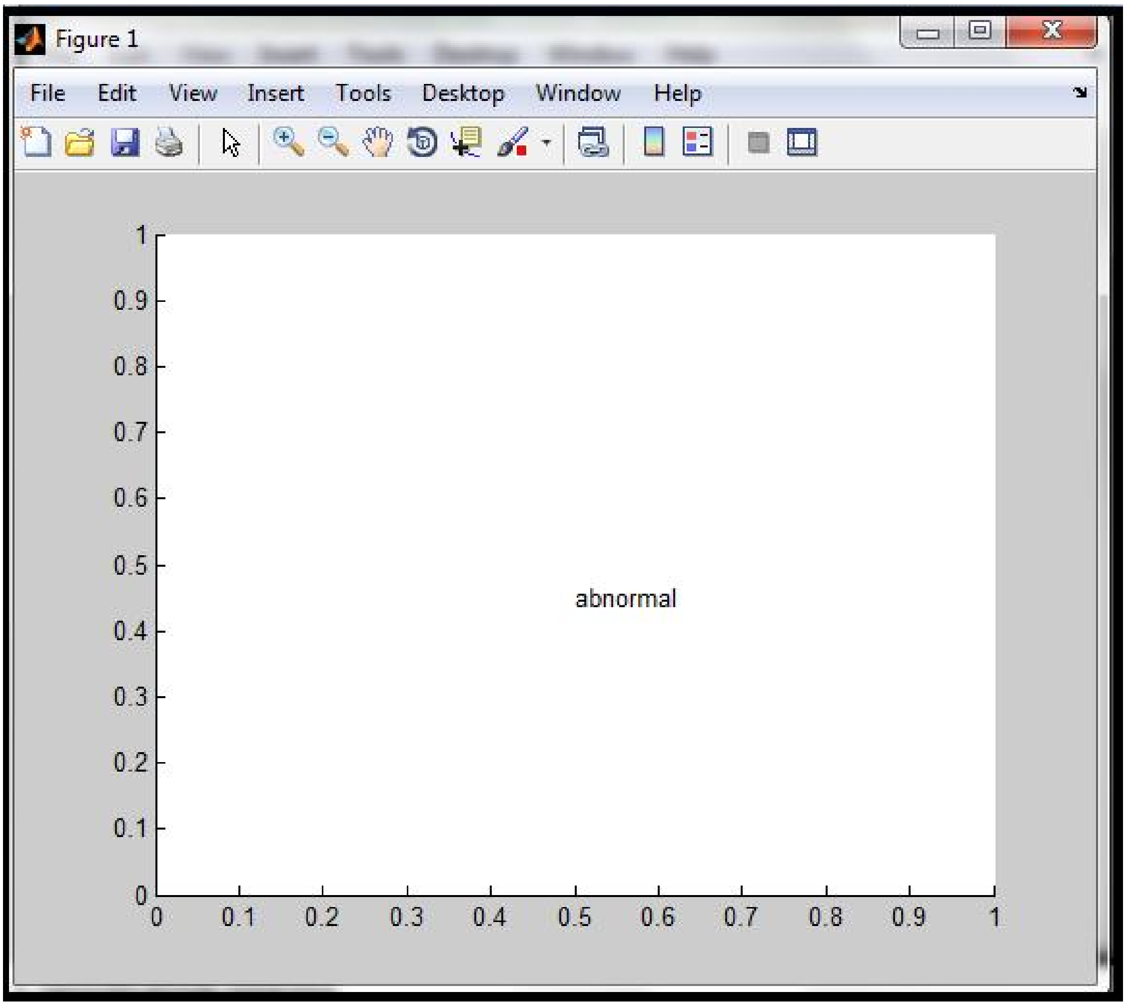


Figure (4.15b): illustrates the classification of abnormal signal.

From comparative features, the classification process was realized by look-up table and classify signal into abnormal case which illustrated in above figure.

Table [4.3]: Features of Heart Sounds (Experimental phase-Real time)

Number	Signal Name	Kurtosis(K)	Variance(V)	Standard deviation (STD)	Mean(M)	Euclidean distance	Classification process match/mismatch
1	Volunteer1 normal	33.911	0.1269	0.3562	0.2062	16	matched
2	Volunteer 2 normal	33.988	0.0917	0.3029	0.1805	9	matched
3	Volunteer3 normal	16.607	0.1184	0.3441	0.2136	16	matched
4	Volunteer4 normal	18.189	0.1019	0.3192	0.1959	11	matched
5	Volunteer5 normal	25.072	0.0746	0.2731	0.1455	07	matched
6	Volunteer6 normal	17.145	0.0815	0.2856	0.1722	08	matched
7	Volunteer7 normal	32.457	0.1673	0.4091	0.2492	21	matched
8	Volunteer8 normal	26.840	0.1266	0.3557	0.2255	16	matched
9	Volunteer9 normal	36.94	0.1016	0.3188	0.1810	12	matched
10	Volunteer10 normal	37.072	0.2182	0.4671	0.2427	27	matched
11	Volunteer11 normal	13.667	0.1329	0.4646	0.2474	19	matched
12	Volunteer12 normal	16.057	0.0852	0.2919	0.1795	09	matched

13	Volunteer13 normal	18.630	0.1032	0.3213	0.1604	10	matched
14	Volunteer14 normal	18.402	0.2572	0.5071	0.2782	18	matched
15	Volunteer15 normal	542.37	1.1244	1.0604	0.2878	195.7	mismatched normal case
16	Volunteer16 normal	165.45	0.3349	0.3002	0.3002	44	mismatched normal case
17	Volunteer17 normal	28.336	0.4259	0.6526	0.3813	42	mismatched normal case
18	Volunteer18 abnormal	80.7540	6.9392	2.6342	1.1301	112	matched
19	Volunteer19 abnormal	63.9222	7.45165	2.8543	1.3212	622	matched
20	Volunteer20 abnormal	220.0299	3.01080	1.7352	1.0123	531	matched
21	Volunteer21 abnormal	92.0420	58.5835	7.6540	1.7723	128	matched
22	Volunteer22 abnormal	75.8037	1.9649	1.4018	1.0001	221	matched
23	Volunteer23 abnormal	126.9965	2.6516	1.6284	1.0002	375	matched
24	Volunteer24 abnormal	422.6092	2.2290	1.4930	1.1021	396	matched
25	Volunteer25 abnormal	175.1813	3.2764	1.8101	1.1120	380	matched
26	Volunteer26 abnormal	289.6853	1.1672	1.0804	0.7493	258	matched
27	Volunteer27	197.5645	0.5959	0.7719	0.4441	98	matched

28	Volunteer28 abnormal	17.5414	0.0742	0.2723	0.1720	09	mismatched abnormal case
29	Volunteer29 abnormal	52.5287	0.0415	0.2036	0.0560	05	mismatched abnormal case
30	Volunteer30 abnormal	44.5008	0.1074	0.3277	0.1432	08	mismatched abnormal case

The threshold for classification cases as normal case:

In order to classify real time cases, from experiments, it was frequently observed for normal cases, the threshold for Euclidean distance is <=27, and thresholds for (mean, standard deviation and variance are <= 1), where the kurtosis threshold is <=40. Otherwise the case classified to abnormal case.

In classification stage, the control signal was selected from **normal offline**.

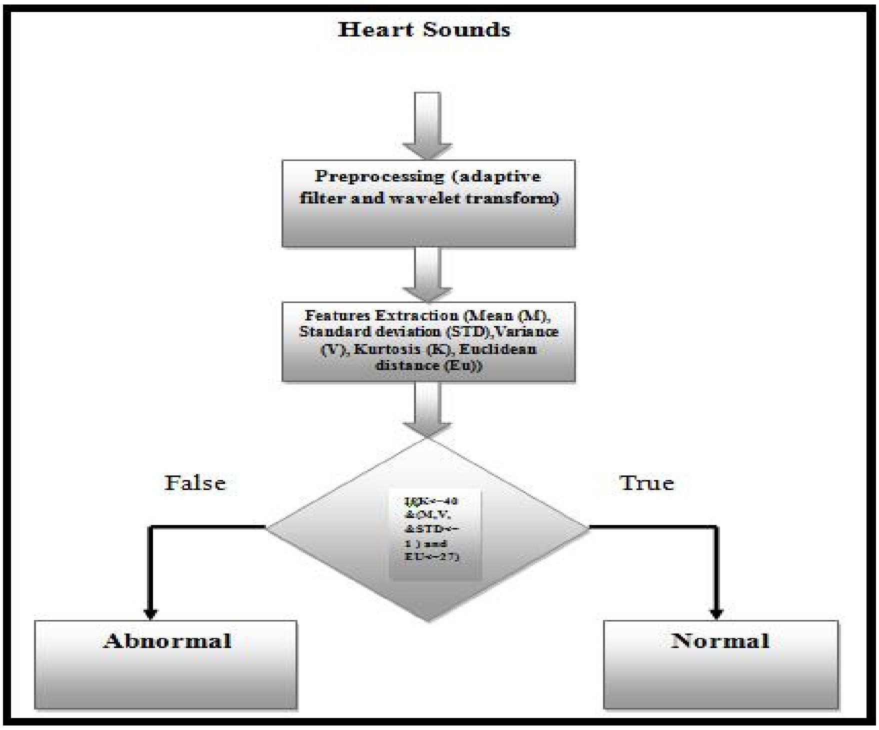


Figure (4.16b): classification algorithm.

4.2.4 Verification result for experimental phase

4.2.4.1 Predictive values:

Now to verify result of online data, calculate the true positive value (TP), false positive value (FP), true negative value (TN), and false positive value (FN) from algorithm results which applied in real data to calculate sensitivity, specificity and accuracy of the system.

Table [2.4]: Predictive values (TP, TN, FP and FN) of the system

statement	normal	abnormal	Total
Positive	14 (True Positive)	10 (True Negative)	24 $T_{\text{Test Positive}}$
Negative	03 (False Positive)	03 (False Negative)	06 $T_{\text{Test Negative}}$
	17 T_{normal}	13 T_{abnormal}	30 Total

Prevalence of normal = Total $_{\text{normal}}$ \ Total *100 (1b)

Prevalence of normal cases = 17\ 30 * 100 = 56.66%

4.2.4.2 Accuracy and sensitivity of the system algorithm:

Sensitivity is the probability that algorithm was classified 'normal' among those with the normal cases.

Sensitivity = TP/ (TP+FP) × 100 (2b)

Sensitivity = 14/(14+3) × 100 = 82.4%

Specificity is the fraction of those abnormal cases, which have a negative algorithm result.

$$\text{Specificity} = FN / (FN + TN) \times 100 \qquad (3b)$$

$$\text{Specificity} = 03/(03+13) \times 100 = \underline{\underline{18.75\%}}.$$

Accuracy:

Accuracy is how close a measured value is to the actual (true) value.

$$\boxed{\text{Accuracy} = \frac{\text{Number of correct samples}}{\text{Number of all samples}} * 100\%} \qquad (4b)$$

Accuracy= 24/30 *100 =$\underline{\underline{80\%.}}$

4.3 RESULT C: Simulation Results for Hardware design flow

The three steps involved in simulation of hardware design flow are described below.

(i) The SIMULINK model of the system is made using the appropriate tool boxes from the SIMULINK library browser.

(ii) From the simulation parameter tool bar the Real Time Workshop (RTW) is used, and the box is filled by the Target System Configuration file. The Run and built buttons are pressed. It will take the MATLAB main window a few seconds to generate the .tlc file. Once it is finished Code Composer Studio (CCS) opens automatically. Now user can link and copy all files which generated by RTW into CCS project.

(iii) CCS converts the source file to assembly code, with ability to loads the generated machine code onto the DSP and runs the DSP automatically. The assembly code can also be loaded manually on the target CPU (the chip) by pressing the Load Program pop up menu in the file menu of CCS.

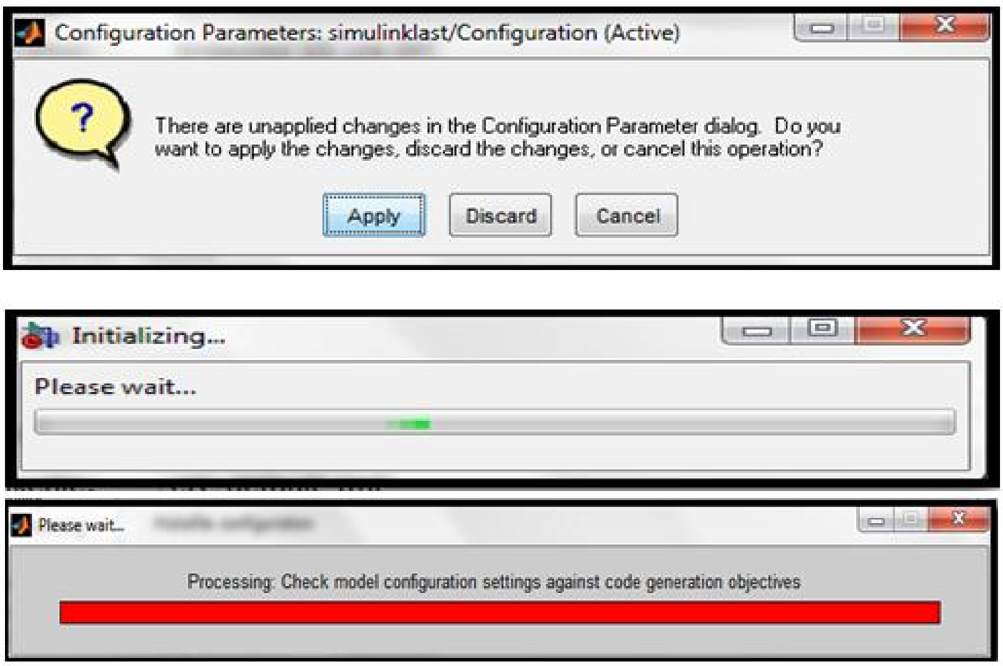


Figure (4.1c): processing results for generating embedded coder.

After code generation is complete, a detailed code generation report opens. Now user can link and copy all files which generated by RTW into CCS project. CCS Software converts the source file to assembly code, with ability to loads the generated machine code onto the DSP and runs the DSP automatically.

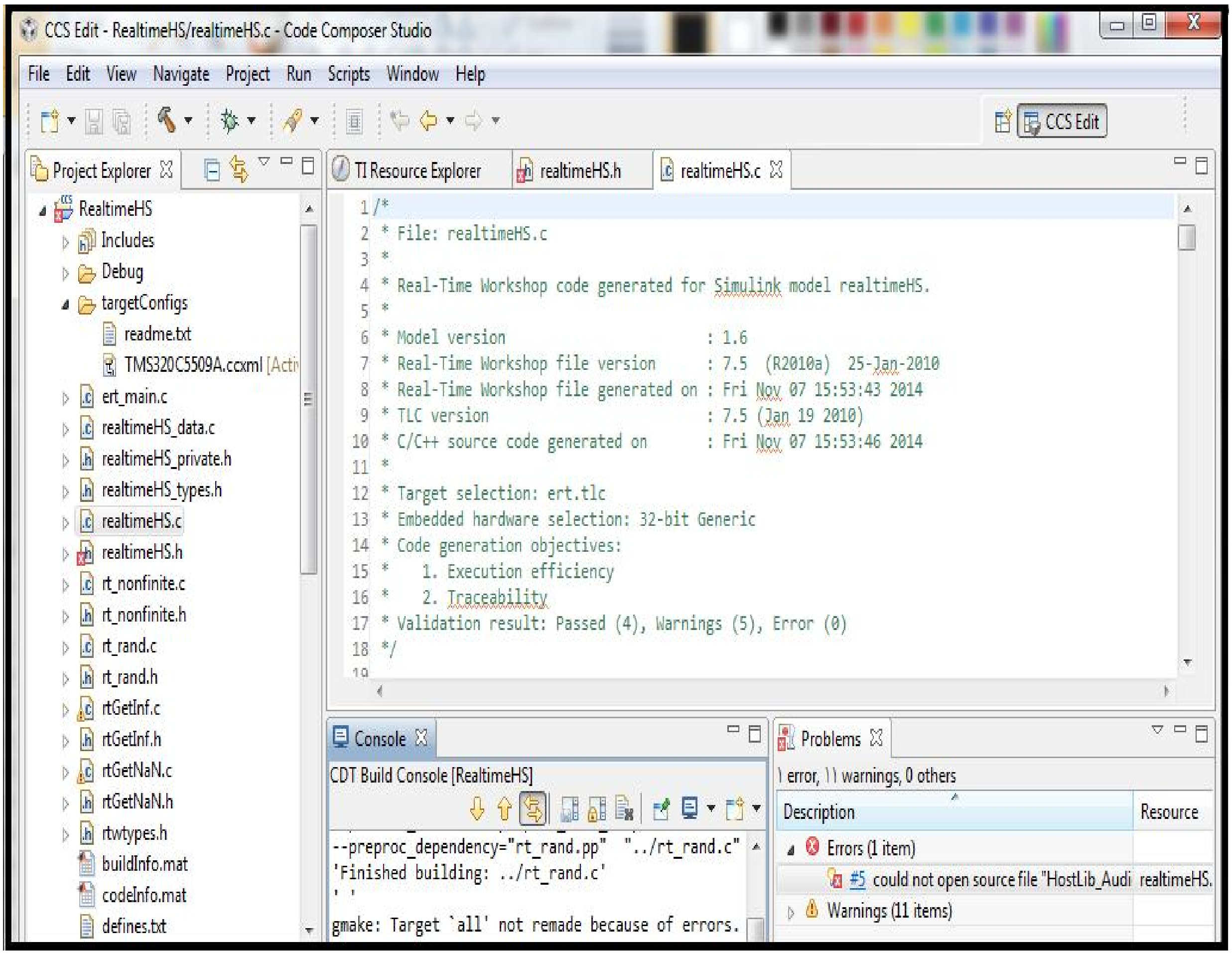


Figure (4.2c): CCS Results for building and running project.

4.4 Summary of Results and Discussion

From literature reviews it was observed, the most recent studies have been applied in off line data.

This project differs from other projects in many features: the sound signal is transferred to PC in a real time, which enabling the user to hear sound directly and record it. And also it introduced processing and analysis tools to classify heart sound into normal and abnormal cases. While some of other projects doesn’t support using PC such as parameswary retna project that it requires only using oscilloscope instead to see the amplified signal in real time.

Wah W. Myint and Bill Dillard in their study in USA also used (specgram) function in MATLAB. They applied an algorithm on tow specific systolic murmurs only. Where the abnormality in this study consist multi cases such as (atrial fibrillation, aortic stenosis, atrial stenosis , summation gallop, and..etc).

This research introduced the designing methods for implementing a portable module based on DSP-Processor, which support medical field in telemedicine applications. Where the most recent studies introduced the implementation algorithm based on PC.

In this study the implementation algorithm produced accuracy of 90%, and sensitivity of 87.5% for offline data, where accuracy is 80% and sensitivity is 82.4% for online data. The percentages of verification results differ on offline and online data due to quality of recording signal, which effected by environmental record and materials selected in order to design of electronic stethoscope. On the other hand the system was a accomplished accuracy and sensitivity more efficient than research of Heart sound classification uses wavelet transform and incremental selforganizing map, by Zümray Dokur and Tamer Ölmez (accuracy 64.7% and sensitivity 70.5%), and less than research of Automatic heart sound signal analysis with Reused Multi-Scale Wavelet Transform, by JiZhong and Fabien Scalzo (accuracy 92%).

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

5.1Conclusions

A reliable Real Time Heart sounds recognition system has been introduced, designed, implemented and successfully tested.

The system algorithm has been applied for offline data and real time data.

In preprocess stage, the signal was filtered from lung sounds and background noise, then the graphical and statistical methods were used to analysis the heart sounds and extract features to be applied in classification process, finally the look-up table was used to classify heart sounds into normal and abnormal cases.

The advanced steps to implement prototype module for embedded DSP processor has been successfully achieved. By building SIMULINK system model and using real time workshop to generate compatible embedded coder for Code Composer Studio.

The algorithm produced accuracy of 90%, and sensitivity of 87.5% for offline data. Where accuracy is 80% and sensitivity is 82.4% for online data.

5.2 Recommendations

The recommendations are to:

Build data base for different heart sounds, including normal and abnormal sounds, to be used for students training and simulation of different heart sounds.

Improve the classification process by identify the abnormality cases that support the treatment decisions.

Implement a prototype module by using Embedded DSP platform (TMS320VC5509A) which supports telemedicine applications.

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[1] F. Debjais, L.G. Durand, Z. Ouo, R. Guarlo, Time–frequency analysis of heart murmurs. Part II: Optimization of time–frequency representations andperformance evaluation, Med. Biol. Eng. Comput. 35 (1997) 480–485.

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APPENDIX A

A1: FIR filter

Finite impulse response filter “digital filter” the design methods .Thus, no previous outputs needs to be saved or to be used for computing .some of the technical areas in which FIR filters are employed include speech recognition and enhancement ,audio recording and equalization ,telecommunication ,signal and data smoothing ,and ultrasound imaging.

By selecting FIR filter using only the a coefficients, you usually require many more coefficients than the corresponding IIR filters .The increase in the number of coefficients from using an FIR filter instead of IIR filter means that more memory and computations are required[37]

A2: IIR filter

This digital filter has a gain curve that approximates the filter characteristics of a corresponding analog filter .IIR filters are used in many areas of many technologies. Some of the application areas are for sound and music enhancement telecommunication, video image processing, biomedical instrumentation and radar and sonar processing.

They are used primarily where analog filters are used .However, implementation on a processor allows much more flexibility ,eliminates degradation, and produces a specific accuracy based on the number of bits used, as well as perfect filter reproducibility[37]

APPENDIX B

B: Adaptive filters

An adaptive filter is a digital filter that has self-adjusting characteristics .It is capable of adjusting its filter coefficients automatically to adapt the input signal via an adaptive algorithm [34].

There are four main component of an adaptive filter Fig c.1. the input or “reference” signal x(n); the output of the adaptive filter y(n); the desired filter response or “primary “signal d(n); and the estimation error e(n), which is the difference between the filter output and the desired response [34].

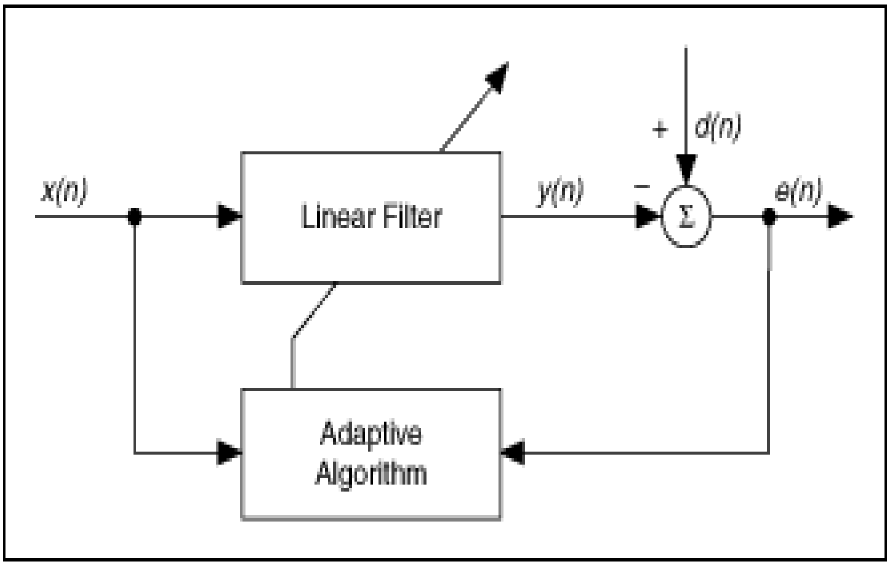

Figure (B.1): adaptive filter structure.

The output y(n) Fig.b.2 is generated as a linear combination of the delayed samples of the input sequence x(n) according to the equation:

$$y(n) = \sum_{i=0}^{N-1} w_i(n)\, x(n-i)$$

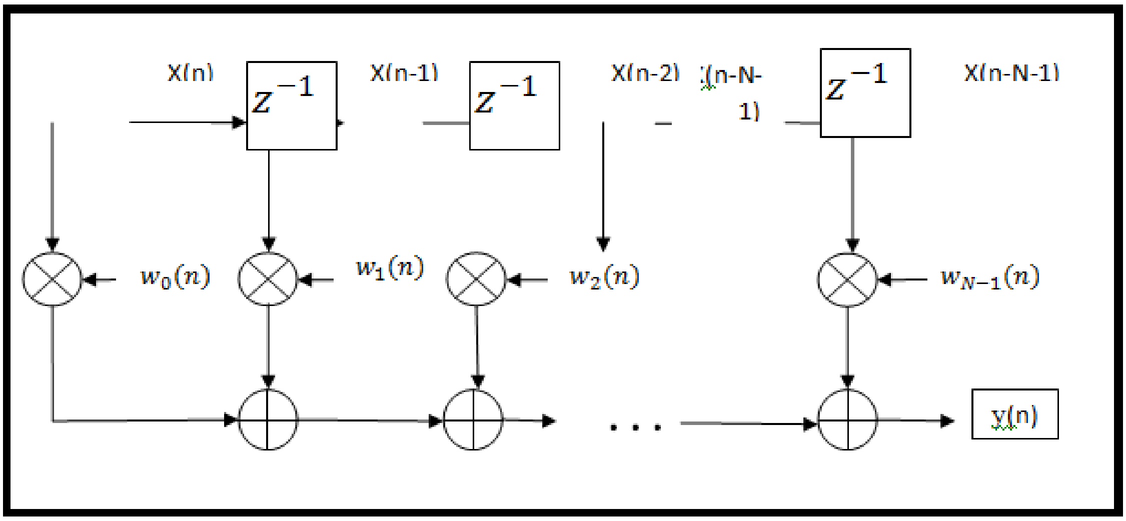

Figure (B.2): y(n) generated as a linear combination of the delayed samples of the input sequence x (n)

where the $w_i(n)$s are the filter tap weights (coefficients) and N is the filter length. We refer to the input samples x(n-i), for i = 0,1,. . . ,N -1 , as the filter tap inputs. The tap weights, the $w_i(n)$ s, which may vary' in lime, are controlled by the adaptation algorithm [20].

With many adaptive filters to choose from, two main consideration frame the decision _ the filter job to do and the filter algorithm to use[34].

The most popular adaptive algorithms are the least mean square (LMS) algorithm and the recursive least square (RLS) algorithm [11].

LMS

The Least Mean Square (LMS) algorithm, introduced by Widrow and Hoff in 1959 is an adaptive algorithm, which uses a gradient-based method of steepest decent. LMS algorithm uses the estimates of the gradient vector from the available data. LMS incorporates an iterative procedure that makes successive corrections to the weight vector in the direction of the negative of the gradient vector which eventually leads to the minimum mean square error [35].

RLS

The Recursive least squares (RLS) adaptive filter is an algorithm which recursively finds the filter coefficients that minimize a weighted linear least squares cost function relating to the input signals [37].

The standard RLS algorithm performs the following operations to update the coefficients of an adaptive filter:

1. Calculates the output signal y(n) of the adaptive filter.
2. Calculates the error signal $e(n)$ by using the following equation:

$$e(n) = d(n) - y(n).$$

3. Updates the filter coefficients using the following equation:

$$\boldsymbol{w(n+1) = w(n) + e(n).K(n)}$$

Where **w(n)** is the filter coefficients vector and **K(n)** is the gain vector.

$$\boldsymbol{K(n)} = \frac{\boldsymbol{P(n).u(n)}}{\boldsymbol{\lambda + u^T(n).p(n).u(n)}}$$

Where λ is the forgetting factor and ***P*(*n*)** is the inverse correlation matrix of the input signal.

The **RLS** algorithm Don't only depend on the initial value but also use the previous value by using the forgetting factor. The value range of the forgetting factor is (0, 1]. When the forgetting factor is less than **1**, this factor specifies that this algorithm places a larger weight on the current value and a smaller weight on the past values

***P*(*n*)** has the following initial value ***P*(0)**:

$$\begin{bmatrix} \delta^{-1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \delta^{-1} \end{bmatrix}$$

here δ is the regularization factor. [37]

$$\boldsymbol{p(n+1) = \lambda^{-1} p(n) - \lambda^{-1} K(n).u^T(n).p(n)}$$

APPENDIX C

C1: Fourier Transform

The Fourier transform is only able to retrieve the global frequency content of a signal, the time information is lost. It's the most popular transformation, it's decomposes a periodic wave in to its component frequencies.

Defined as:

$$X(f) = \int_{-\infty}^{+\infty} x(t).e^{-2\pi jft}$$

t = time parameter.   f = frequency parameter.

Disadvantages:

- Not suitable for transient signals with sharp changes.
- Time information difficult to retrieve.

C2: Short time Fourier transforms:

It's calculates the Fourier transform of a windowed part of the signal and shifts the window over the signal. The short time Fourier transform gives the time-frequency content of a signal with a constant frequency and time resolution due to the fixed window length. This is often not the most desired resolution. For low frequencies often a good frequency resolution is required over a good time resolution. For high frequencies, the time resolution is more important. A multi-resolution analysis becomes possible by using wavelet analysis. The continuous wavelet transform is calculated analogous to the Fourier transform, by the convolution between the signal and analysis function. However the trigonometric analysis functions are replaced by a wavelet function.

Defined as:

$$X(t,f) = \int_{-\infty}^{+\infty} [x(t).\omega(t-t').e^{-2\pi jft}.dt$$

APPENDIX D

D: Wavelet

A wavelet is a short oscillating function which contains both the analysis function and the window. Time information is obtained by shifting the wavelet over the signal. The frequencies are changed by contraction and dilatation of the wavelet function. The continuous wavelet transform retrieves the time-frequency content information with an improved resolution compared to the STFT [38].

Daubechies Wavelets DbN:

This family consist the hear wavelet, db1, which is the simplest and certainly the oldest, it's discontinuous, resembling acquire form.

The Hear wavelet is defined by

$\varphi(x) = 1 \; if \;\; x = \in \;\; [0,0.5], \varphi(x) = -1 \; if \;\; x \in [0.5,1] \; and \; 0 \; if \;\; it \; not$:

The associated scaling function is the function:

$\phi(x) = 1$ if $x \in [\, 0 \, , 1]$ and 0 if not [38].

Dbn properaties:

- Symmetric.
- The regularity increase with order.
- The analysis is orthogonal.

Three cases make wavelet the more useful

1- Wavelets constitute a mathematical "zoom" making it possible to simultaneously describe the properties of a signal on several timescales.

2- Wavelets create very simple algorithms that, due to their adaptability, are often more powerful and easy to tune than the traditional methods of functional estimation. The principle consists of calculating the wavelet transform of observations, then astutely modifying the coefficients profiting from their local nature and, finally, inversing the transformation.

3- Wavelets constitute a very competitive method. Due to generally very sparse representations, they make it possible to reduce the volume of information to be coded.

- In 1D the signal is decomposed into two: an approximation and a detail

Discrete wavelet transform

Discrete wavelet transform (DWT) uses filter banks to perform the wavelet analysis. The discrete wavelet transform decomposes the signal into wavelet coefficients from which the original signal can be reconstructed again. The wavelet coefficients represent the signal in various frequency bands. The coefficients can be processed in several ways, giving the DWT attractive properties over linear filtering [38].

Wavelet Defined as:

$$\gamma(s,\tau) = \int f(t)\psi^{*}{}_{s,\tau}(t)d(t)$$

Inverse Wavelet Transform Defined as

$$f(t) = \int\int \gamma(s,\tau)\Psi_{s,\tau}(t)d\tau d(s)$$

All wavelet derived from *mother wavelet*

$$\Psi_{s,\tau}(t) = \frac{1}{\sqrt{s}}\,\Psi(\frac{t-\tau}{s})$$

If $h_i(n)$ is an orthogonal filter and $g_i[n] = h_i[-n]$ then we have an orthogonal wavelet transform.

Wavelet Decomposition:

- A *single level decomposition* puts a signal through 2 complementary low-pass and high-pass filters
- The output of the low-pass filter gives the approximation (A) coefficients, while the high pass filter gives the detail (D) coefficients

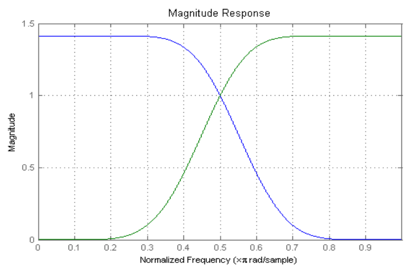

Figure (D.1): low and high pass filter

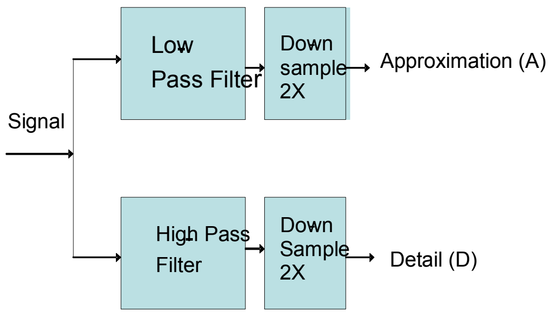

Figure (D.2): approximation and details

Wavelet Reconstruction:

The A and D coefficients can be used to *reconstruct* the signal *perfectly* when run through the mirror reconstruction filters of the wavelet family[38].

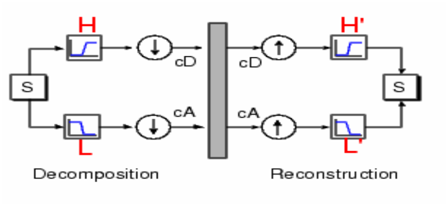

Figure (D.3): decomposition and reconstruction

The wavedec() function performs 1D multilevel Discrete Wavelet Transform decomposition of given signal and returns ordered list of coefficients arrays in the form:

[cA_n, cD_n, cD_n-1... cD2, cD1]