# FETAL ECG EXTRACTION USING WIENER, SVD AND ICA ALGORITHMS

*Thesis submitted in partial fulfilment of the requirements for the degree*

*By*


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In
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# CERTIFICATE

This is to certify that the work in the thesis entitled **"FETAL ECG EXTRACTION USING WIENER, SVD AND ICA ALGORITHMS"** by **Raja N Reddy Kommareddy (211EC3311)** is a record of an original research work carried out by him under my supervision and guidance in partial fulfilment of the requirements for the award of the degree of Master of Technology with specialization in *Electronics and Instrumentation* from the department of *Electronics and Communication Engineering*, National Institute of Technology Rourkela. Neither this thesis nor any part of it has been submitted for any degree or academic award elsewhere.

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Successful completion of work will never be one man's task. It requires hard work in right direction. There are many who have helped to make my experience as a student a rewarding one. In particular, I express my gratitude and deep regards to my thesis guide **Dr. UMESH CHANDRA PATI** for kindly providing me to work under his supervision and guidance. I extend my deep sense of indebtedness and gratitude to him first for his valuable guidance, constant encouragement & kind co-operation throughout period of work which has been instrumental in the success of thesis. I am greatly indebted to my family members for extending their loving support throughout. I bow to the Devine power, who led me all through.

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# ABSTRACT

Fetal Electrocardiogram (FECG) signal recording is one of the best techniques for Heart signal monitoring of fetus. It is also used to monitor health condition of fetus in pregnancy period continuously. Fetal electrocardiogram is nothing but wave form which shows electrical activity of fetus's heart. FECG is extracted from a signal recorded on the mother's abdomen, which is an indirect method (non-invasive method). Abdomen signal includes mother electrocardiogram (MECG) signal, FECG signal and noise signal.

Different indirect methods to extract the Fetal Electrocardiogram (FECG) signal from an ECG recorded on the mother's abdomen have been proposed. In this thesis, three methods are used, which are as follows: Singular Value Decomposition (SVD) method, Independent Component Analysis (ICA) method, and Weiner Filtering method. Wiener filter uses the linear least square estimation; SVD uses the variance as measure which is similar to Eigen value decomposition and ICA uses the fourth order moment, kurtosis. SVD and ICA are comes under statistical domain and also blind source separation, whereas Wiener filter comes under Fourier domain.

The mentioned methods use signal processing techniques for extracting FECG from Abdominal Electrocardiogram (AECG) and uses a multi-channel data/signal. The advantages and disadvantages of each method are discussed. The methods have applied on synthetic ECG signals of 10 seconds with a sampling rate of 256Hz. Efficiencies of all the methods are compared together based on the few important criterions, which are output waveform, PSD, and SNR. The results are stated and best method based on the criterions is selected.

Keywords: FECG extraction, SVD, ICA, Wiener filter, PSD, SNR

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# LIST OF ABBREVIATIONS

| | |
|---|---|
| FECG | Fetal Electrocardiogram |
| SVD | Singular Value Decomposition |
| PCA | Principle Component Analysis |
| ICA | Independent Component Analysis |
| BSS | Blind Source Separation |
| FHR | Fetal Heart Rate |
| MIT-BIH | Massachusetts institute of technology-Beth Israel Hospital |
| AECG | Abdominal Electrocardiogram |
| MECG | Maternal Electrocardiogram |
| SNR | Signal to Noise Ratio |

# CHAPTER 1

# INTRODUCTION

INTRODUCTION

LITERATURE SURVEY

OBJECTIVE

THESIS ORGANIZATION

This chapter is the preface to rest of the thesis. This comprises of a brief introduction to FECG extraction followed by literature survey which includes all the important contributions to the field of FECG signal analysis. The rest part of this chapter contains objective of the thesis and thesis organization.

## 1.1 INTRODUCTION

During pregnancy period health condition of fetus must be continuously monitored, to keep the fetus healthy. By monitoring continuously the clinical specialists can increase their level of attendance and in emergency situations they can take a better decision quickly. For this one of the best techniques is heart signal monitoring which gives us important information about fetal health condition.

Electrical potentials produced by heart are graphically recorded as ECG (Electro-Cardio-Gram). The electrical potentials are generated by simultaneous repolarization and depolarization of cells due to $Na^+$ and $K^+$ ions momentum in the blood. The range of ECG signal is typically 2mv and requires 0.1 to 120 Hz recording bandwidth. ECG is acquired by placing electrodes at standard locations on the skin which comes under non-invasive technique. Heart rate and ECG reflects the health of human heart. The duration and amplitude of the PQRSTU wave gives the useful information about the health of the heart. An ideal FECG is shown in Figure 1.1 [1].

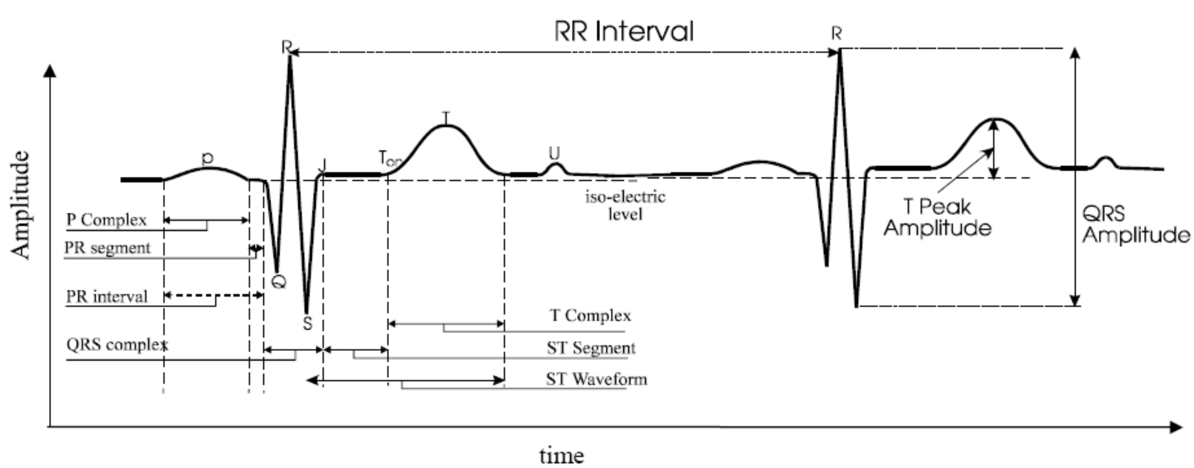


Figure 1.1: An ideal FECG.

For heart signal monitoring of fetus one of the best techniques is Fetal Electrocardiogram (FECG) signal recording, which can be used to monitor health condition of fetus in pregnancy period continuously. Fetal electrocardiogram is nothing but wave form which shows electrical activity of fetus's heart. Most diseases of fetus are discovered in FECG.

Fetal electrocardiogram can be obtained in two ways: direct method and in-direct method. In direct method, the electrode should pass through abdomen of mother and enter the womb to touch the fetus's head. This may cause some problems to both mother and fetus. Hence nowadays indirect method is used for recording FECG, i.e. FECG is extracted from a signal recorded on the mother's abdomen. In-direct method is shown in Figure 1.2.

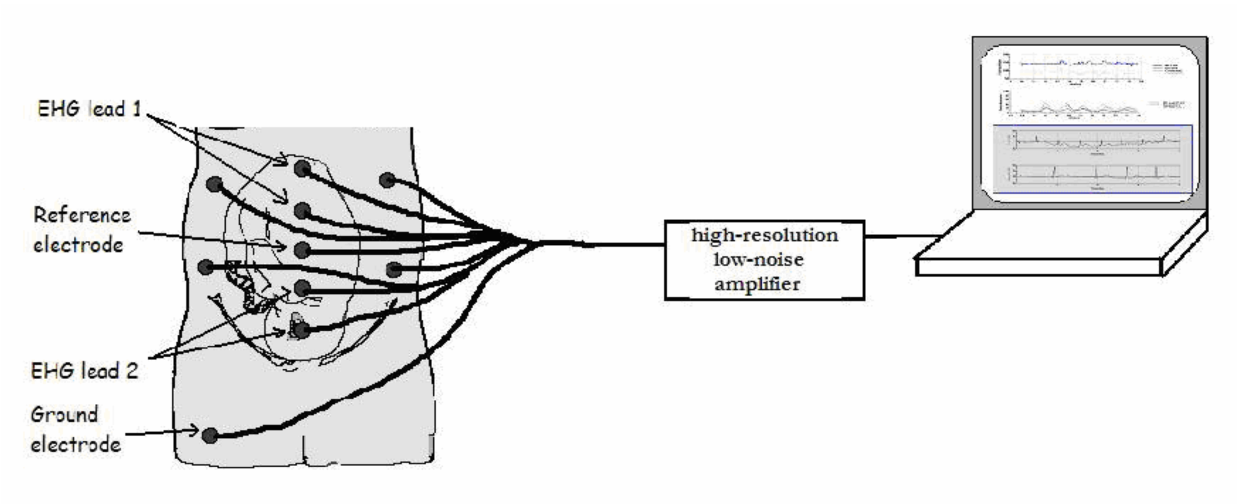


Figure 1.2: Recording abdominal signal.

Abdomen signal includes mother electrocardiogram (MECG) signal, Fetal electrocardiogram (FECG) signal and noise signal. Noise signal includes muscular noise, electrodes noise, base lines noise and recording system noise. In-direct method also has some difficulties such as permanent appearance of Mother's ECG signal which dominates FECG as it is 5-20 times bigger in amplitude which is considered as noise in Fetal ECG extraction. A recorded abdominal signal is shown in Figure 1.3 [1]. There are so many signal processing techniques which include adaptive filtering, independent component analysis, singular value decomposition, wavelet based techniques etc., for extracting FECG from AECG.

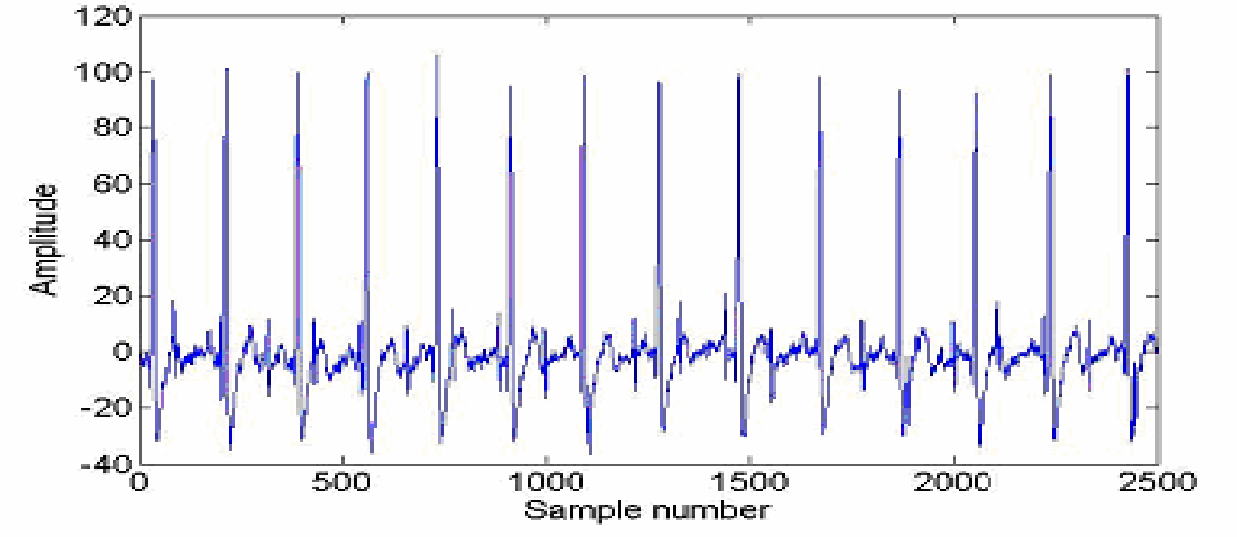


Figure 1.3: Recorded AECG signal

## 1.2 LITERATURE SURVEY

S. Sargolzaei, K. Faez and A. Sargolzaei [1] used SVD, ICA, Wavelet based methods and Adaptive filtering methods, to extract FECG on both synthetic and real signals, and also mentioned their advantages and disadvantages.

P. P. Kanjilal, S. Palit and G. Saha [2] applied SVD on single channel composite maternal ECG signal to extract Fetal ECG signal at low SNR.

V. Zarzoso, J. M. Roig and A. K. Nandi [3] used a BSS method based on higher-order statistics is contrasted with a significant classical technique for FECG extraction, such as Widrow's multi-reference adaptive noise cancellation and also optimal Wiener-Hopf filtering solutions. Both procedures are applied to real multi-channel ECG recordings obtained from a pregnant woman.

K. V. K. Ananthanag and J. S. Sahambi [4] BSS used methods based on higher order statistics which are not influenced by the electrode placement. All the algorithms were able to extract E C G considerably if the amount of the input SNR was high.

P. Gao, E. C. Chang and L. Wyse [5] applied Singular Value Decomposition (SVD) on the spectrogram, followed by an iterated application of Independent Component Analysis OCA) on the principle components. The SVD contributes to the separability of each component and the ICA contributes to the independence of the two components.

R. Sameni, C. Jutten, and M. B. Shamsollahi [6] applied the JADE ICA algorithm to the data, from the 8 extracted components, 4 clearly corresponded to the maternal heart, 2 with the fetal heart, and 2 with noise.

G. D. Clifford [7] explained the methods of Blind Source Separation which includes PCA and ICA techniques, and also explained the different methods to achieve them with advantages and disadvantages.

M. A. Hassan, M. B. I. Reaz, M. I. Ibrahimy, M. S. Hussain and J. Uddin [8] made a review paper on various methodologies and developed algorithms on FECG signal and its nature for fetal monitoring. Also they carried out the study of the performance and accuracy of various methods for FECG signal analysis.

## 1.3 OBJECTIVE

Long term FECG monitoring and detailed analysis of the FECG during labor and pregnancy could provide valuable information about the health conditions of the fetus and to assist clinicians in reducing incidents of unnecessary medical intervention. It is very important during the pregnancy and labor to monitor continuously the FECG. Therefore, the aim is to provide maximum possible information about the FECG. For that the objectives chosen are

- To apply three methods namely wiener Filter, SVD and ICA to detect and extract the FECG signal from composite AECG signal for efficient FECG monitoring.
- To compare the mentioned three methods basing on output waveform, PSDs of the output waveform and SNR, to state the best method for the purpose.

## 1.4 THESIS ORGANIZATION

The thesis constitutes five chapters including this chapter. The rest of the thesis is organized as follows:

**Chapter 2: Heart and its electrical conduction system**

This chapter deals with the different parts of heart and their functions in estimating status of the heart. Electrical conduction system of heart and conduction paths of cardiac action potentials along with the bundle of HIS and its importance are discussed.

**Chapter 3: FECG and its noises**

This Chapter explains the morphology of the FECG signal and noises affecting the FECG signal. Basics of FECG monitoring techniques and FECG detection and extraction are discussed, and also discussed about the importance and usefulness of the FECG data base.

**Chapter 4: FECG detection and extraction algorithms**

This chapter discusses different approaches which are implemented in this thesis to extract the FECG signal from the AECG signal, which includes Wiener Filter, SVD and ICA techniques. Also in this chapter, the AECG signal and other signals required for the FECG signal extraction, which are taken from MIT-BIH database, are shown. Then, the AECG signal (FECG + MECG + NOISE) are passed through the Wiener Filter, SVD and ICA and their outputs are discussed. This chapter also compares the three techniques basing on the SNR and PSD of the outputs of the three techniques.

**Chapter 5: Conclusions and future scope**

This chapter presents analytical remarks to overall achievements and limitations of all the proposed methods, states the best method among the above stated methods which can be efficiently extract the FECG from abdominal ECG and also gives the idea about the further research work that can be done in this domain.

## 1.5 SUMMARY

The need for FECG extraction and analysis, the work done related to this field and different methods to extract FECG from AECG, the objective taken for the FECG extraction and analysis and the thesis organization are discussed, which are the guidelines to the rest of the thesis.

# CHAPTER 2

# HEART AND ITS ELECTRICAL CONDUCTION SYSTEM

HEART

HEART BEAT

ELETRICAL CONDUCTION SYSTEM

BUNDLE OF HIS

## 2.1 HEART

The heart is a muscular organ about the size of a fist, located between the lungs in the middle of the chest, just behind and slightly left of the breastbone. The heart pumps blood through the network of arteries and veins called the cardiovascular system. Heart has 4 chambers: The upper two chambers are called the left atrium and right atrium, and the lower two chambers are called the left ventricle and right ventricle. The left and right atria and the left and right ventricles are separated by a wall of muscle called the septum. In the heart left ventricle is the largest and strongest chamber. The walls of left ventricle's chamber are only about a half inch thick, but they have enough force to push blood through the aortic valve and into the body. Heart physical structure is shown in the Figure 2.1.

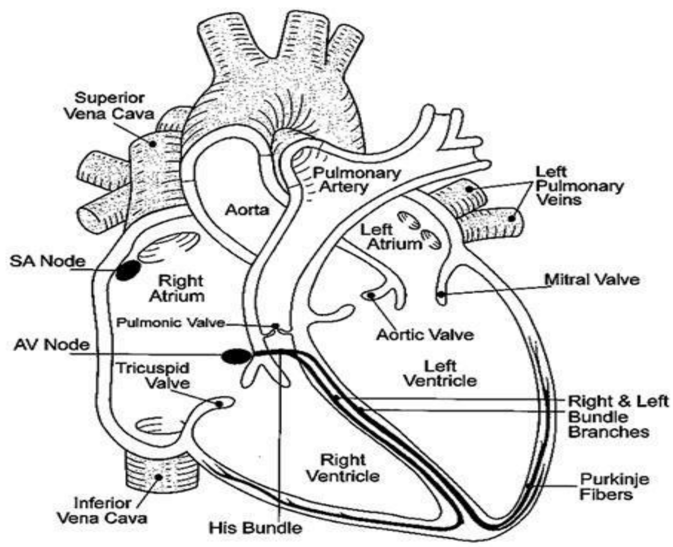


Figure 2.1: Heart

The right atrium receives blood from the veins and pumps it to the right ventricle. The right ventricle receives blood from the right atrium and pumps it to the lungs, where it is loaded with oxygen. The left atrium receives oxygenated blood from the lungs and pumps it to the left ventricle. The left ventricle (the strongest chamber) pumps oxygen-rich blood to the rest of the body. The left ventricle’s vigorous contractions create our blood pressure.

The coronary arteries run along the surface of the heart and provide oxygen-rich blood to the heart muscle. A web of nerve tissue also runs through the heart, conducting the complex signals that govern contraction and relaxation. Surrounding the heart is a sac called the pericardium. Four types of valves regulate blood flow through the heart:

- Blood flow between the right atrium and right ventricle is regulated by valve called the tricuspid valve.
- Blood flow from the right ventricle into the pulmonary arteries is controlled by the pulmonary valve, which carry blood to the lungs to pick up oxygen.
- Flow of Oxygen-rich blood from the lungs from the left atrium into the left ventricle is regulated by the mitral valve.
- The way for oxygen-rich blood to pass from the left ventricle into the aorta is done by the aortic valve. Aorta human body's largest artery delivers blood to the rest of the body.

Heart does not work alone; brain tracks the conditions around such as climate, stress, and level of physical activity and adjusts the cardiovascular system to meet those needs.

## 2.2 HEART BEAT

A heart beat is a two-part pumping action that takes about a second. As blood collects in the upper chambers (the right and left atria), the heart's natural pacemaker (the SA node) sends out an electrical signal that causes the atria to contract. This contraction pushes blood through the tricuspid and mitral valves into the resting lower chambers (the right and left ventricles). This part of the two-part pumping phase (the longer of the two) is called diastole [19].

The second part of the pumping phase begins when the ventricles are full of blood. The electrical signals from the SA node travel along a pathway of cells to the ventricles, causing them to contract. This is called systole. As the tricuspid and mitral valves shut tight to prevent a back flow of blood, the pulmonary and aortic valves are pushed open. While blood is pushed from the right ventricle into the lungs to pick up oxygen, oxygen-rich blood flows from the left ventricle to the heart and other parts of the body.

After blood moves into the pulmonary artery and the aorta, the ventricles relax, and the pulmonary and aortic valves close. The lower pressure in the ventricles causes the tricuspid and mitral valves to open, and the cycle begins again. This series of contractions is repeated over and over again, increasing during times of exertion and decreasing while at rest. The heart normally beats about 60 to 80 times a minute when the body is at rest, but this can vary. It is usually lower in people who are physically fit and it rises as the people become older.

## 2.3 ELECTRICAL CONDUCTION SYSTEM OF THE HEART

Electrical impulses from the heart muscle (the myocardium) cause the heart to beat (contract). This electrical signal begins in the Sino-atrial (SA) node, located at the top of the right atrium. The SA node is sometimes called the heart's "natural pacemaker." When an electrical impulse is released from this natural pacemaker, it causes the atria to contract. The signal then passes through the atrio-ventricular (AV) node. The AV node checks the signal and sends it through the muscle fibers of the ventricles, causing them to contract [17]. The SA node sends electrical impulses at a certain rate, but the heart rate may still change depending on physical demands, stress, or hormonal factors. Different action potentials produced by different parts of the heart are shown in the Figure 2.2.

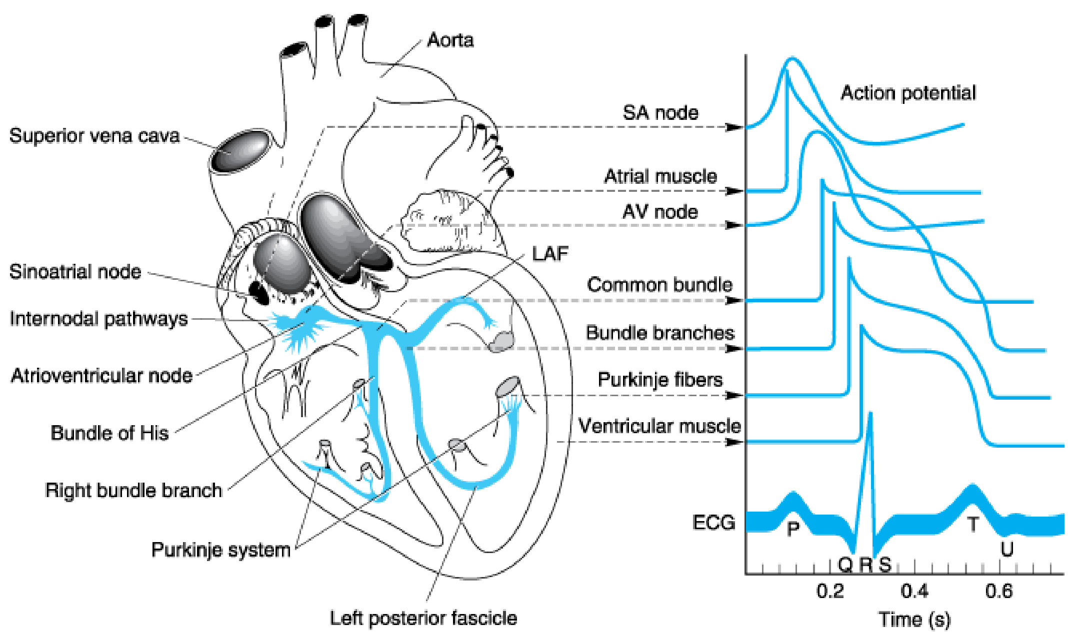


Figure 2.2: Cardiac action potentials

## 2.4 BUNDLE OF HIS

The bundle of His is a collection of heart muscle cells specialized for electrical conduction that transmits the electrical impulses from the AV node (located between the atria and the ventricles) to the point of the apex of the fascicular branches. The fascicular branches then lead to the Purkinje fibers which provide electrical conduction to the ventricles, causing the cardiac of the ventricles to contract at a paced interval. The conduction paths of cardiac action potentials are show in Figure 2.3.

The bundle of His is an important part of the electrical conduction system of the heart as it transmits impulses from the atrio-ventricular node, located at the inferior end of the inter-atrial septum, to the ventricles of the heart. The intrinsic rate of the Bundle of His is between 40-60 bpm. The bundle of His branches into the left and the right bundle branches, which run along the inter-ventricular septum. The left bundle branch further divides into the left anterior and the left posterior fascicles. These bundles and fascicles give rise to thin filaments known as Purkinje fibers. These fibers distribute the impulse to the ventricular muscle [18]. Together, the bundle branches and Purkinje network comprise the ventricular conduction system. It takes about 0.03-0.04s for the impulse to travel from the bundle of His to the ventricular muscle.

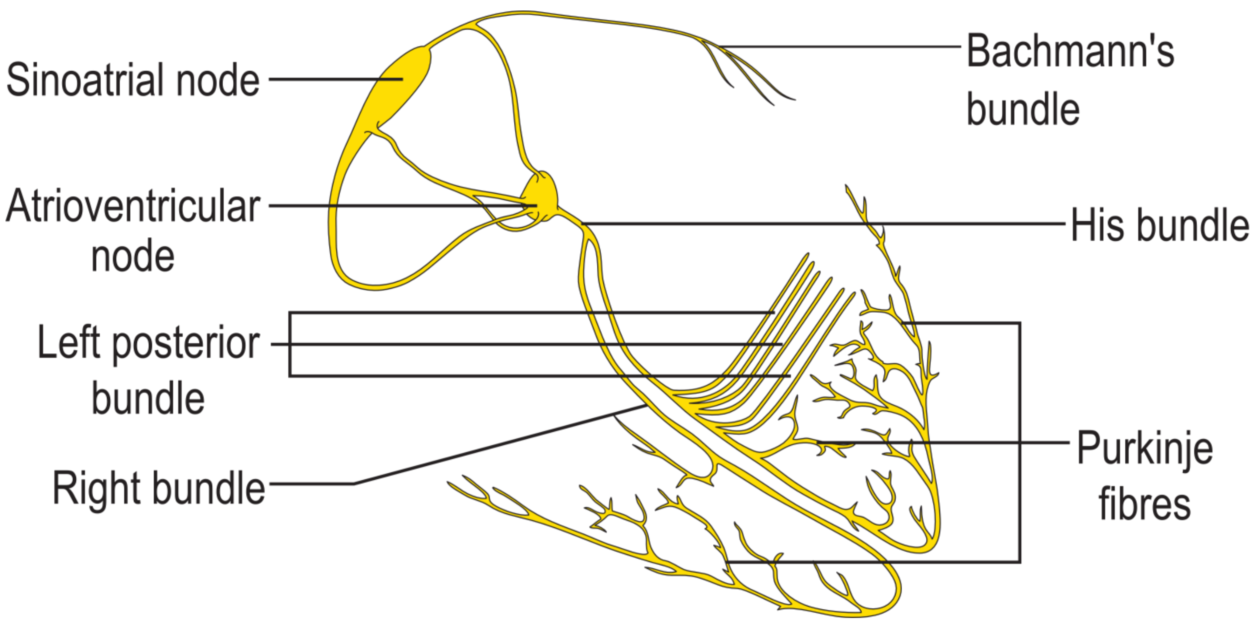


Figure 2.3: Conduction paths of cardiac action potentials

Electrical activity in the normal human heart is initiated when a cardiac action potential arises in the Sino atrial (SA) node, which is located in the right atrium. From there, the electrical stimulus is transmitted via inter-nodal pathways to the atrio-ventricular (AV) node. After a brief delay at the AV node, the stimulus is conducted through the bundle of His to the left and right bundle branches and then to the Purkinje fibers and the endocardium at the apex of the heart, then finally to the ventricular myocardium.

The AV node serves an important function as a "gatekeeper", limiting the electrical activity that reaches the ventricles. In situations where the atria generate excessively rapid electrical activity (such as atrial fibrillation or atrial flutter), the AV node limits the number of signals conducted to the ventricles. For example, if the atria are electrically activated at 300 beats per minute, half those electrical impulses may be blocked by the AV node, so that the ventricles are stimulated at only 150 beats per minute, resulting in a pulse of 150 beats per minute). Another important property of the AV node is that it slows down individual electrical impulses. This is manifested on the electrocardiogram as the PR interval (the time from electrical activation of the atria to electrical activation of the ventricles), which is usually less than 120 milliseconds in duration.

## 2.5 SUMMARY

The function of heart and its different parts with their individual functions are studied. Electrical conduction system of heart studied here gives the idea of ECG and its different properties. Cardiac action potentials of different parts of heart summing up to ECG gives the status of individual parts of the heart and exact position in the heart where the problem is can be known.

# CHAPTER 3

# FECG AND ITS NOISES

This chapter explains the basics of FECG and the noises affecting it briefly. It also explains the FECG monitoring techniques, importance of FECG detection and extraction, and finally FECG database.

## 3.1 FECG MORPHOLOGY

Reliable and vital information about the condition of the fetus during pregnancy and labor is given by FECG, which is nothing but biomedical signal that gives electrical representation of Fetus heart beat from the recordings on the mother's abdomen. The FECG signal is a comparatively weak signal (less than 20% of the mother ECG) and often embedded in AECG and noise. The FECG lies in the range from 1.3 to 3.5 Hz and sometimes it is possible for the mother and some of the FECG signals to be closely overlapping [8]. The FECG monitoring enables accurate measurement of fetal cardiac performance including transient or permanent abnormalities of rhythm.

For early stage diagnostic of fetus health and to know its status, sometimes the FECG is the only information source. The FECG is very much related to the mother ECG i.e., MECG, containing the same basic waveforms including the P wave, the QRS complex, and the T wave [10] [11]. The PQRST complex as shown in Figure 3.1 is an electric signal produced by the contraction and relaxation of the fetus' heart's muscles.

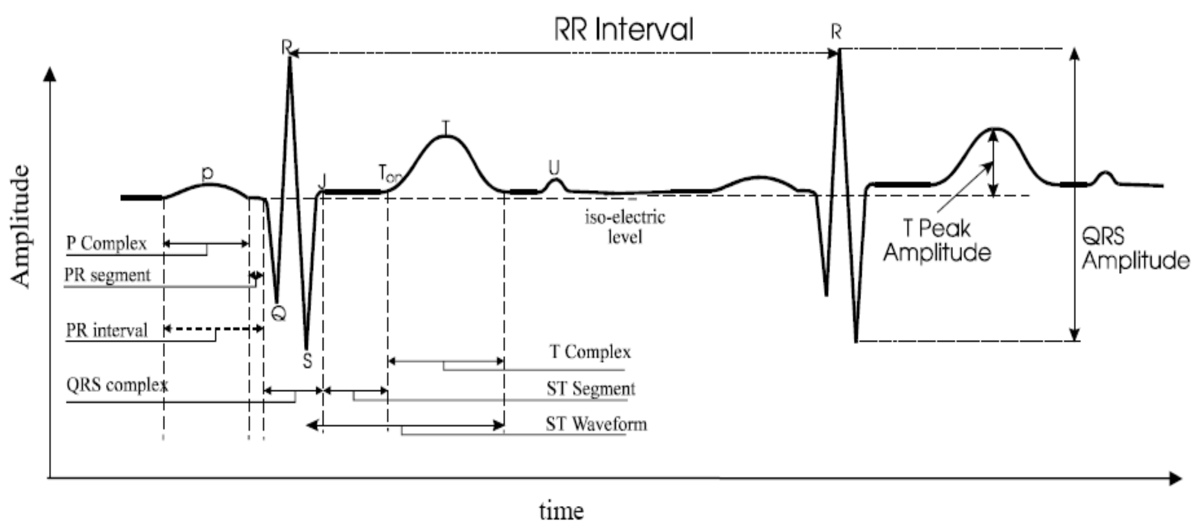


Figure 3.1: PQRST complex of FECG

It is composed of three parts; the P wave occurs due to the depolarization of the atria, the QRS complex is due to the rapid depolarization of both ventricles. The muscles of the ventricles have large muscle mass than that of atria, hence its amplitude is much larger than that of P wave which is extremely reliable and the T wave corresponds to the ventricular repolarization phase, which follows each heart contraction. The R–R interval leads to the heartbeat frequency that gives useful information for the heart condition. The FECG signal detected and extracted from the maternal abdomen typically has low amplitude and an unfavourable signal-to-noise ratio from which the FHR can hardly be detected.

## 3.2 NOISES AFFECTING FECG

The FECG exhibits a bandwidth of 0.05–100 Hz. In an abdominal register, the maximum amplitude of the QRS usually oscillates from 100 to 150 μV for the maternal recording and up to 60 μV for the fetal recording [8]. Common ECG noise sources, such as power line interference, muscle contractions, respiration, skin resistance interference, and instrumental noise, in addition to electromyogram and electrohysterogram due to uterine contractions, can corrupt FECG signals significantly. Therefore, it is important to understand the characteristics of the electrical noise. Electrical noise, which will affect FECG signals, can be categorized into the following types:

**Power line interference:** Power line interference occurs through two mechanisms: capacitive and inductive coupling. Power line interference consists of 60-Hz pickup and harmonics, which can be modelled as sinusoids and combination of sinusoids [9]. Capacitive coupling is responsible for high frequency noise while inductive coupling introduces low frequency noise. For this reason inductive coupling is the dominant mechanism of power line interference in electro cardiology. To limit the amount of power line interference, electrodes should be applied properly, that there are no loose wires, and all components have adequate shielding.

**Electrode contact noise:** Variations in the position of the heart with respect to the electrodes causes electrode contact and also with the changes in the propagation medium between the heart and the electrodes. Poor conductivity between the electrodes and the skin reduces the amplitude of the FECG signal and decreases the signal-to-noise ratio, which is due to the disconnection of the measurement system from the subject. The modelling of electrode contact noise can be considered as randomly occurring rapid baseline transition, which has a superimposed 60-Hz component and decays exponentially to the baseline value.

**MECG signal:** In the FECG extraction MECG is the most predominant interfering signal for FECG in the abdominal ECG signal. The frequency spectrum of the MECG signal partially overlaps the FECG and therefore filtering alone is not sufficient to remove the MECFG signal for extracting FECG from abdominal ECG.

**Maternal muscle noise:** The motion of the leg and abdominal muscles are the cause for muscle noise and may be picked up from the reference pad on the maternal thigh. Uterus is the source of this kind of noise. Sometimes, it is very difficult to identify the EMG signal in the abdominal ECG signal.

**Motion artifact:** The usual causes of motion artifact are movement, vibrations, or respiration of the subject. The information is skewed when motion artifact is introduced to the system. One of the sources for irregularities in the data is motion artifacts. Electrode interface and electrode cable are two main sources for motion artifact. By proper design of the electronic circuitry and setup motion artifact can be reduced.

**Ambient noise:** The source for the ambient noise is electromagnetic radiation. Electric magnetic radiations from the earth are constantly effects the surfaces of the human bodies and on the surface of earth it is virtually impossible to avoid exposure to ambient noise.

**Inherent noise in electronics equipment:** All the electronic equipment's generate noise. It can only be reduced by using high quality electronic components but complete elimination of this noise is not possible.

## 3.3 FECG MONITORING TECHNIQUES

Fetal heart rate analysis has become a widely accepted means of monitoring fetal status. The most familiar means of acquiring the FHR is Doppler ultrasound. In addition, the FHR monitoring is also done by considering fetal magneto cardiogram (FMCG) that uses superconducting quantum interference device magnetometers. Apart from this, fetal phonocardiography (FPCG) allows the heart sounds to be detected for FHR monitoring. The majority of FHR analysis technique is performed using a bedside monitor over a relatively short period, with the mother to be in a recumbent position [8]. All of the above techniques that are mentioned have been successfully used for FHR monitoring, although the initial choice was which of the above techniques would be employed. Obviously, a fetal scalp electrode cannot be used ante- partum period as there is a great risk to cause a mark or small cut on the fetal head; the instrumentation required for the acquisition of the FMCG is too cumbersome for ambulatory use; while fetal phonocardiography was felt to be too susceptible to movement artifacts effects. Therefore, the Doppler ultrasound and the abdominal FECG (as it is commonly referred to) are the most viable options for the monitoring of FHR.

Currently, Doppler ultrasound and FECG have proven to be reliable techniques for monitoring FHR. The FHR monitoring using the Doppler ultrasound is widely used and appropriate be- because an invasive test cannot be used daily. The advantage of the Doppler ultrasound technique is that it can be virtually assured that a recording of FHR will be obtained. The disadvantages of such systems require intermittent repositioning of the transducer and they are only suitable for use with highly trained midwifes. The ultrasound transducer is problematic and uncomfortable while the procedure involves launching a 2-MHz signal towards the fetus.

The use of Doppler ultrasound (non-invasive manner) is not suitable for long periods of FHR monitoring. This may involve skilful placement and continual repositioning of the transducer, which would be a severe problem for long-term ambulatory use. It may cause records of uncertain accelerations or decelerations and true abrupt changes can be misinterpreted as noise. The major limitation of the Doppler ultrasound technique is its sensitivity to movement. The movement of the mother can result in Doppler-shifted reflected waves, which are stronger than the cardiac signal. This Doppler ultrasound technique is inappropriate for long term monitoring of the FHR, as it requires the patients to be bed-rested. Moreover, the detection of the heartbeat using Doppler ultrasound relies upon a secondary effect (the mechanical movement of the heart) and is therefore not as accurate for beat-to-beat analysis as detection of the QRS complex. Allied to this drawback is the fact that most Doppler systems rely upon some form of averaging to produce their FHR data.

In contrast, methods utilizing the abdominal electrocardiogram (AECG) have a greater prospect for long-term monitoring of FHR and fetal well-being using signal processing techniques. The AECG signal can also be used for antepartum non-invasive FHR determination through the detection of small fetal cardiac potentials at the surface of the maternal abdomen. The AECG can be used to produce true R–R interval data, which is suitable for heart rate variability studies if required. Its advantage is that it is completely non-invasive and unobtrusive, has comparatively low power requirements, and can be used over extended (e.g., 24 h) periods. The method additionally allows the maternal heart rate (MHR) to be recorded since the MECG is also detected from the AECG. It is advantageous of using AECG to extract FECG with the additional information compared to using Doppler ultrasound. Some new highly accurate techniques are reported for monitoring the FHR.

The major disadvantage with this technique is that the acquisition of the FECG cannot be guaranteed and often has a very low signal-to-noise ratio (SNR) because of the interference caused by MECG, electromyogram (EMG), and motion artifact in determining the FHR from the AECG signal. To overcome the above problems, some multiple-lead algorithms use the thoracic MECG to cancel the abdominal MECG, though this is inconvenient for the patient during long term monitoring. Hence, to make the AECG suitable for the detection of the FECG, the SNR must be enhanced. The decision was therefore made to base the investigation on the possibility of constructing an ambulatory FHR recorder around the acquisition of the abdominal FECG.

The FECG is an electrical signal that can be obtained noninvasively by applying a pair of electrodes to the abdomen of a pregnant woman. Therefore, detection of FECG signals with powerful and advance methodologies is becoming a very important requirement in biomedical engineering for the interest in FECG signal analysis in clinical diagnosis and biomedical applications. The FECG contains potentially valuable information that could assist clinicians in making more appropriate and timely decisions during labor, but the FECG signal is vulnerable to noise and difficulty of processing it accurately without significant distortion has impeded its use. A number of difficulties and complication are associated with recording the AECG. The signal processing algorithm needs to remove the MECG complexes, reduce the effects of motion artifact, muscle noise, and power line interface, and then enhance the fetal QRS complexes before they can be consistently detected. Therefore, to get proper information of the FHR and fetal status, it is necessary to improve the SNR of the abdominal signal.

Methods of extracting FECG from the AECG have been recently introduced for the monitoring of FECG signal. These methods can be classified with respect to the principle ideas of signal processing as follows: threshold technique, spectral analysis, linear combinations, or weighted sums. The extraction of FECG from the complex signal (mother and fetus) can be reframed in a more efficient manner using blind source separation (BSS) methods such as principal component analysis and independent component analysis (ICA).

## 3.4 FECG DETECTION AND EXTRACTION

There are two methods of recoding FECG signal, one is direct recording and second one is in-direct method. First method needs the electrode to be pierced in to the mother womb, which is dangerous to both mother and fetus. Hence the FECG recording without direct contact with fetus is desirable and it is called non-invasive technique. The extraction of FECG is very important to get the reliable information about fetal status and to detect abnormalities, to enable the measure for assuring fetal well-being, to check whether the fetus is alive or dead, and to determine twin pregnancies.

In the indirect method of recording, the FECG signals have a very low power relative to that of the MECG and noises. The method of recording FECG signal is far worse during the uterine contractions of the mother. During these contractions, the AECG recordings will be corrupted by other electrophysiological signals called uterine electromyogram (EMG), which are due to motion of the uterine muscle rather than due to the heart. The response of the fetal heart to the uterine contractions is an important indicator of the fetal health. But monitoring the FECG during these contractions is a difficult task because of very poor SNR. The three main characteristics that need to be obtained from the FECG extraction for useful diagnosis of the fetal condition includes; FHR, Amplitude of the different waves and Duration of the waves.

In the non-invasive method of measurement of the FECG, most of the signal processing algorithms detects only the R waves and the P and T waves will not be detected. And also, by using regular filtering techniques cannot solve FECG extraction problem easily. Linear filtering in the Fourier domain fails since the spectral content of all the three components, MECG, FECG, and noise, are rather similar and overlap.

## 3.5 FECG DATA BASE

Since 1975, the laboratories at Boston's Beth Israel Hospital (now the Beth Israel Deaconess Medical Centre) and at Massachusetts Institute of Technology (MIT) have supported the research in arrhythmia analysis and related subjects by creating a database. One of the first major products of their effort was the Massachusetts Institute of Technology Beth Israel Hospital (MIT-BIH) database [13]. This database was completed and began distributing in 1980.

PhysioNet, the on-line component of the Research Resource for Complex Physiologic Signals, where we can find the data, software, and reference materials, is part of MIT-BIH

Database Distribution. One of the data bases is Non-invasive Fetal Electrocardiogram Database, which consists of a vector of the recorded ECG signal in mVs, sampled at a rate of 256 Hz. This includes AECG, noise, ideal FECG, etc.

It's laboratory is the Laboratory for Computational Physiology, is part of the Harvard-MIT Division of Health Sciences and Technology, which collaborate closely with colleagues at the Margret & H.A. Rey Laboratory for Nonlinear Dynamics in Medicine at Boston's Beth Israel Deaconess Medical Center, the Center for Polymer Studies at Boston University, Boston's Hebrew Rehabilitation Center for Aged, the Laboratory of Biomedical Computer Systems and Imaging at the University of Ljubljana (Slovenia) the National Research Council (CNR) Institute of Clinical Physiology in Pisa (Italy), and the Center for Nonlinear Dynamics in Physiology and Medicine at McGill University.

## 3.6 SUMMARY

FECG morphology gives the idea of what are the parameters to be considered for its detection, extraction and analysis. The FECG monitoring techniques gives the idea of what are parameters and noises will be involved while recoding the signal. By knowing the noises affecting it, the necessary precautions and parameters to be considered are made while the algorithms are formulated. The required signals for testing the algorithms are taken from the FECG data base of MIT-BIH data base.

# CHAPTER 4

# FECG DETECTION AND EXTRACTION ALGORITHNMS

WIENER FILTER

BLIND SOURCE SEPARATION

PRINCIPAL COMPONENT ANALYSIS

INDEPENDENT COMPONENT ANALYSIS

RESULTS AND DISCUSSION

All the algorithms which are implemented in this thesis for FECG extraction purpose are described here. For extraction of FECG from AECG Wiener filter, SVD and ICA techniques are used.

## 4.1 WIENER FILTER

Wiener filters are known as linear optimum discrete-time filters, optimum in the sense of minimizing an appropriate function know as cost function of the error. Mean square error (MSE) is the commonly used cost function in filter design optimization. Minimizing mean square error (MSE) involves only second order statics (correlation) and leads to a theory of linear filtering that is useful in many applications. This approach is common to all optimum filter designs.

The idea here is to recover $d(n)$ a desired signal from a noisy observation $x(n) = d(n) + v(n)$, where both $v(n)$ and $d(n)$ are assumed to be wide sense stationary (WSS) process. The problem can be stated as "design a filter that produces an estimate $\hat{d}(n)$ using a linear combination of the data $x(n)$ such that the mean square error (MSE) function, cost function: $J = E\{(d(n) - \hat{d}(n))^2\} = E\{e^2(n)\}$ is minimized[7].

### 4.1.1 Linear least squares estimation

Depending on the relation of the data $x(n)$ and the desired signal $d(n)$, there are four problems which need solution. These are smoothing, filtering, de-convolution and prediction. Mathematician Norbert Wiener was first person who stated that: given two random signals $x(n)$ and $y(n)$, what is the filter $h(n)$ that does the best job for producing $y(n)$ from $x(n)$? This problem has important applications in both signal conditioning and system modelling. Considering $\hat{y}(n)$ is the estimate of $y(n)$ and obtained by processing $x(n)$ through the filter $h(n)$. Then the best filter $h(n)$ that minimizes the mean power in the error signal is calculated.

Hence the assumption taken is that $h(n)$and $x(n)$are known, and derived an expression for the cross spectrum $S_{xy}(f)$. The best filter minimizes the mean power in the error signal $e(n) = y(n) - \hat{y}(n)$, which is given by

$$P_e = P_y - 2\sum_k h(k)R_{xy}(k) + \sum_k \sum_l h(k)h(l)R_x(k-l) \tag{4.1}$$

The relation between the data $x(n)$ and the estimate $y(n)$ is a linear one; hence it is called linear least squares estimation. The power in the error signal is a quadratic function of the filter coefficients $h(k)$. Therefore it has a single minimum which can be determined by setting to zero the partial derivatives of $P_e$ with respect to the $h(k)$:

$$\frac{\partial P_e}{\partial h(k)} = 0 \tag{4.2}$$

This yields the system of linear equation,

$$R_{xy}(k) = \sum_l h(l) R_x(k-l) h(l) \tag{4.3}$$

It is easily verified and the prediction error can be written as:

$$P_e = P_y - P_{\hat{y}} \tag{4.4}$$

Hence, the power in the desired signal $y(n)$ is the sum of the power in the estimate $\hat{y}(n)$ and the power in the error $e(n)$. Taking $u(n) = \hat{y}(n)$ and $e(n) = v(n)$, implies that $R_{\hat{y}e}(k) = 0$ for all $k$, i.e., that the error signal $e(n)$ is uncorrelated with the estimate $\hat{y}(n)$. Because $\hat{y}(n)$ is a weighted sum of input samples, this also means that the error is uncorrelated with the observations $x(n-k)$, i.e., the $R_{xe}(k) = 0$ equals zero for all k. The result that the error is uncorrelated with the observations is a general property of linear, least-squares estimation which can be used to derive the system of equation (4.3).

### 4.1.2 Non causal wiener filter

Solving the system of equations requires knowledge of $R_{xy}(k)$ and $R_x(k)$ for all k. The exact solution depends on constraints on the filter $h(n)$. For example, if $h(n)$ is constrained to be a causal, FIR filter of length N, i.e. if it is zero outside of the interval $[0,\ N-1]$, reduces to a system of N linear equations with N unknowns that can be solved by standard techniques. (This is what done for the special case $y(n) = x(n+1)$ when deriving the Yule-Walker equations for linear prediction). There is another case in which the solution to is easy to find: When there are no constraints on the filter, i.e., when is to be solved for $-\infty < k < \infty$. In this case, the right side of it is the convolution $R_x(k) * h(k)$, so that a solution can be obtained by means of the Fourier transform:

$$H(f) = \frac{S_{xy}(f)}{S_x(f)} \tag{4.5}$$

$H(f)$ is called the (non-causal) discrete-time Wiener filter [14] [15]. This means that, if $y(n)$ were exactly derived from $x(n)$ by a filtering operation, the filter that provides the least-squares estimate of $y(n)$from $x(n)$would be the actual one. Then the optimal filter for estimating $y(n)$ from the noisy signal $x(n)$is

$$H(f) = \frac{S_{xy}(f)}{S_x(f)} = \frac{S_y(f)}{S_y(f) + S_d(f)}\,, \quad S_d = S_x - S_y \tag{4.6}$$

$H(f) \approx 1$ for frequencies where the signal-to-noise ratio $S_y(f)/S_d(f)$ is large, while $H(f) \approx 0$ when the signal-to-noise ratio is small. Also note that, because power spectra are real and even, $H(f)$ is also real and even, which means that $h(n)$ is symmetric with respect to the origin, and therefore non-causal [16]. In applications that require causality, a causal filter could be obtained by approximating $h(n)$ by a finite impulse response filter, then delaying the impulse response of the FIR filter by half its length.

### 4.1.3 Applications of wiener filter

Wiener filters have two main applications, system identification, and signal conditioning. System identification: the goal is to model the unknown system that produces a known output $y(n)$ from a known input $x(n)$. There are two ways in system identification [7].

Direct system identification: the unknown system and the Wiener filter are placed in parallel, in the sense that both receive the same input $x(n)$. The goal is to find the filter $H(f)$ such that its response $\hat{y}(n)$ to $x(n)$best estimates the output $y(n)$of the unknown filter.

Inverse system identification: the unknown filter and the Wiener filter are placed in series: The output$x(n)$ of the unknown system is used as input to the Wiener filter, and the goal is to make the output of the Wiener filter $\hat{y}(n)$ best estimate the input $y(n)$ to the unknown system. Thus, if $y(n)$and $x(n)$ are related by a filter $G(f)$, the Wiener filter $H(f)$ would ideally be $1/G(f)$.

Signal conditioning: the goal is to either cancel out the noise from a noisy signal, or to detect a signal in additive noise. In both cases, the signal to be estimated y[n] is assumed to be the sum of two uncorrelated components $u(n)$ and $v(n)$. The signal to be filtered $x(n)$ is related to v$(n)$ by an unknown system (and therefore $x(n)$ and $v(n)$ are correlated), but $x(n)$ and $u(n)$ are uncorrelated.

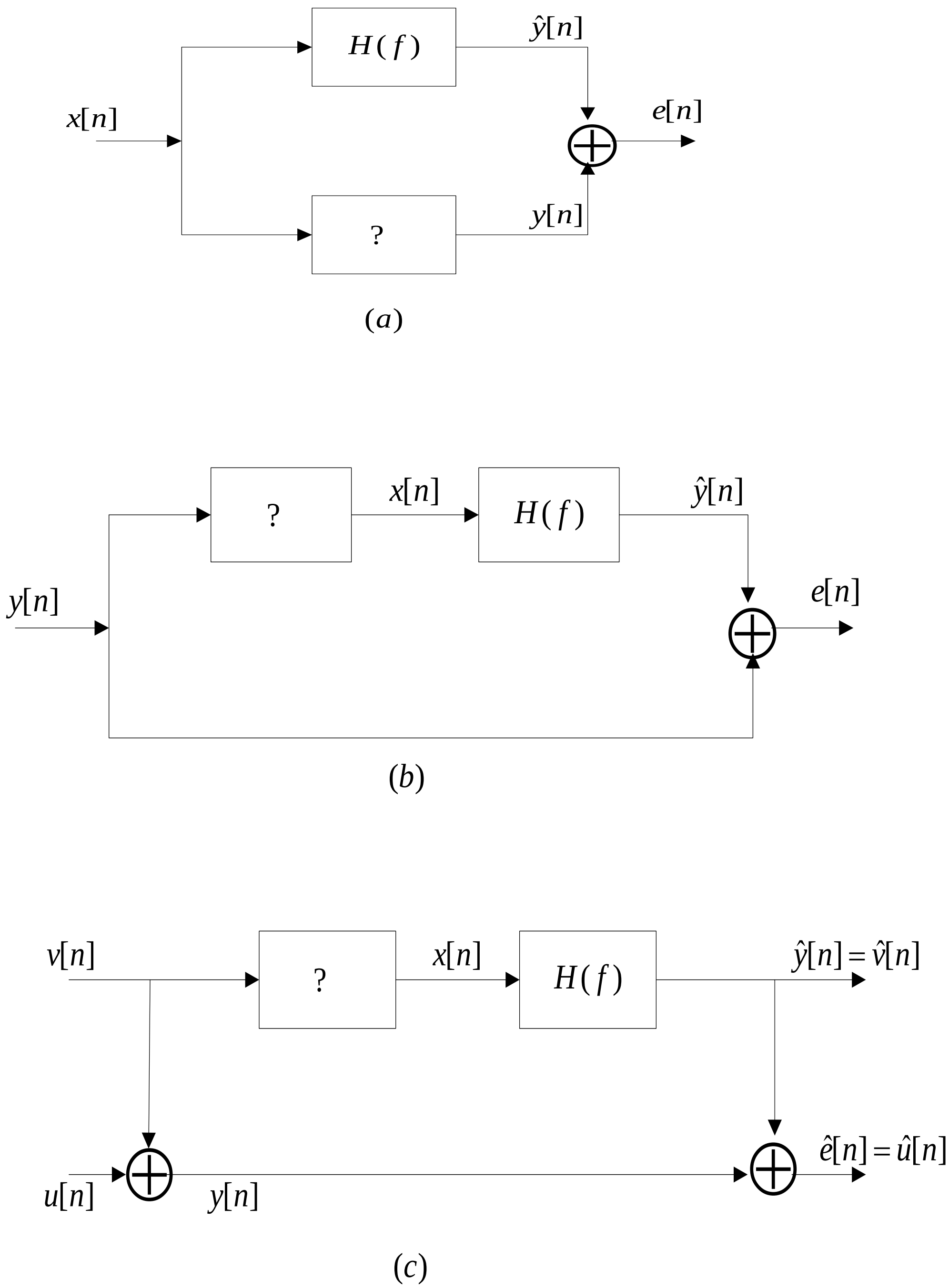


Figure 4.1: (a) Direct system identification. (b) Inverse system identification. (c) Noise cancellation and signal detection.

Detection applications: $v(n)$ is the signal and $u(n)$ is the noise, so that the output $\hat{y}(n)$ of the Wiener filter is effectively an estimate of the signal $v(n)$ from the observations $x(n)$. The error signal $e(n) = y(n) - \hat{y}(n)$ is then an estimate of the noise $u(n)$.

Cancellation applications: $u(n)$ is the signal, and $v(n)$ (and therefore $x(n)$) is noise. Thus, the output $\hat{y}(n)$ of the Wiener filter is an estimate of the noise $v(n)$ from $x(n)$, while the error signal $e(n) = y(n) - \hat{y}(n)$ is an estimate of the signal $u(n)$.This technique can be used, for example, to cancel 60-Hz components from recordings of the electrocardiogram.

The Wiener filter gives the optimum linear estimate of a desired random signal $y(n)$ corrupted by additive noise $d(n)$. To implement this filter, the desired signal $y(n)$ does not have to be known exactly, only its power spectrum is needed. A different kind of optimum filter, the matched filter, is used in applications when the desired signal is known exactly.

## 4.2 BLIND SOURCE SEPARATION

Principal Component Analysis (PCA) using Singular Value Decomposition (SVD), and Independent Component Analysis (ICA), both of these techniques utilize a representation of the data in a statistical domain rather than a time or frequency domain [7]. Difference between these statistical techniques and Fourier-based techniques is that the Fourier components onto which a data segment is projected are fixed, whereas PCA- or ICA-based transformations depend on the structure of the data being analyzed.

Any projection onto another set of axes (or into another space) is essentially a method of separating the data out into separate components or sources which will hopefully allow it to see more clearly in a particular projection. That is, the direction of projection increases the signal-to-noiseratio (SNR)fora particularsignal source.

One important difference between these techniques is that Fourier techniques assume that the projections onto each frequency component are independent of the other frequency components. PCA and ICA attempt to find a set of axes which are independent of one another in some sense. They require assuming that there are a set of independent sources in the data, but not their exact properties. Since they discover, rather than define the new axes, they are known as blind source separation.

PCA uses the variance as the measure to discover the new axes and thus leads to a set of orthogonal axes. Because the data are de-correlated in a second order sense and the dot product of any pair of the newly discovered axes is zero. ICA uses the measure based on non-Gaussianity, such as kurtosis, and the axes are not necessarily orthogonal. Kurtosis is the fourth moment (mean, variance, and skewness are the first three) and is a measure of how non-Gaussian is a probability distribution function (PDF). Large positive values of kurtosis indicate a highly peaked PDF that is much narrower than a Gaussian. A negative kurtosis indicates a broad PDF that is much wider than a Gaussian.

### 4.2.1 Central limit theorem

Adding independent signals together (which have highly non-Gaussian PDFs), will eventually arrive at a Gaussian distribution. Conversely, if a Gaussian like observation is broken down into a set of non-Gaussian mixtures, each with distributions that are as non-Gaussian as possible, the individual signals will be independent. Therefore, kurtosis is to separate non-Gaussian independent sources, whereas variance is to separate independent Gaussian noise sources [7].

PCA de-correlates the signal by projecting the data onto orthogonal axes. However, ICA results in a bi-orthogonal transform of the data and the axes are not necessarily orthogonal. Both PCA and ICA is used to perform lossy or lossless transformations by multiplying the recorded (observation) data by a separation or de-mixing matrix. Lossless PCA and ICA both involve projecting the data onto a set of axes which are determined by the nature of the data, and are therefore methods of blind source separation (BSS).

These techniques once they have discovered the axes of the independent components in the data and have separated them out by projecting the data onto these axes, then these techniques can be used to filter the data. PCA and ICA produces the non-invertible matrices, by setting columns of separation matrices that correspond to unwanted sources to zero. By Forcing the inversion of the separation matrix and transforming the data back into the original observation space, they remove the unwanted source from the original signal.

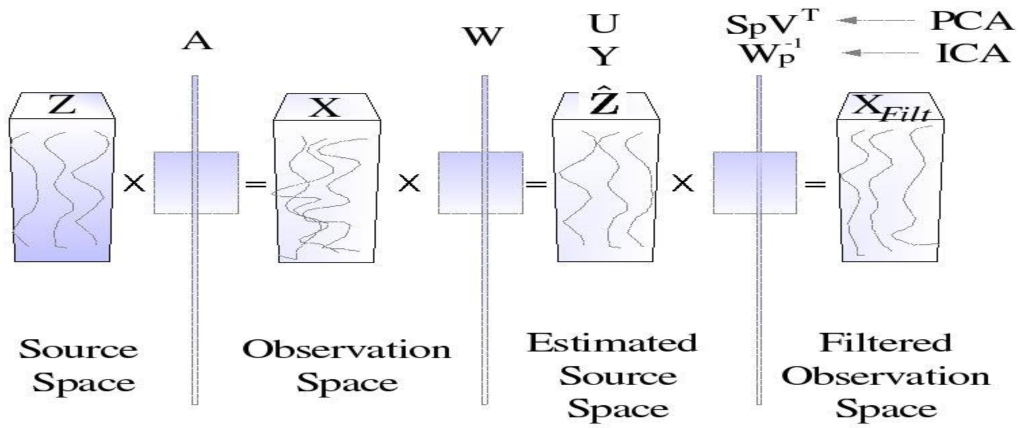


Figure 4.2: Blind source separation for filtering.

The sources are projected from a source space to an observation space to give the observations, X, from the given unknown matrix of sources Z which is mixed by some linear stationary matrix of constants A. These observations are then transposed back into an estimated source space in which the estimates of the sources, $\hat{Z}$ are projected. Then by reducing the dimensionality of the estimated source space i.e., by discarding the estimates of the sources that correspond to noise or unwanted artifacts by setting (N−p) columns of $W^{-1}$ to zero (to give $W_p^{-1}$) and re-projecting back into the observation space. $X_{filt}$ is the resulting matrix of filtered observations. The filtered observation space and original observation space are the same, but the data projected into them is filtered and unfiltered respectively. In the case of PCA, the sources are the columns of U, and are formed using $S^{-1}$ and $V^{T-1}$, but the transformation is not so straightforward. $X_{filt} = U*S_p*V^T$ reconstructs the filtered observations by reducing the dimensionality of S to have only p non-zero columns. Whereas ICA multiplies X with the de-mixing matrix W to reveal the estimates of the sources, $Y = \hat{Z}$. And sets the Columns of $W^{-1}$ to zero to remove the 'noise' sources and by using $X_{filt} = W_p * Y$ the filtered data are reconstructed.

## 4.3 PRINCIPAL COMPONENT ANALYSIS

PCA implements the idea of finding the component vectors $Y_1, Y_2, \ldots\ldots, Y_N$ that explain the maximum amount of variance possible by N linearly transformed components. PCA in an intuitive way uses a recursive formulation. By passing over the data and attempting to maximize the value of $V_1 = \arg\max_{|V|=1} E\{(V_1^T X)^2\}$, where $V_1$ is the same length M as the data X, the direction of the first principal component $V_1$ is found [7]. Thus the first principal component is the projection on the direction in which the variance of the projection is maximized. By repeating this process in the remaining orthogonal subspace each of the remaining $M - 1$ principal components are found (which reduces in dimensionality by one for each new component discovered). $y_i = V_i^T X (i = 1, \ldots\ldots, N)$, the projection of X onto each $V_i$ gives the principal components. This transformation of the columns of X onto $V_i^T$, to give $y_i$ is also known as the (discrete) Karhunen-Lo`eve transform, or the Hotelling transform.

PCA de-correlates the data by performing an orthogonal projection of the data, which reduces the dimension of the data from N to P ($P < N$) to remove unwanted components in the signal. PCA representation is an optimal linear dimension reduction technique in the mean-square sense. One important application of this technique is to noise reduction, where the data contained in the last N - P components is assumed to be mostly due to noise. Another benefit of this technique is that a projection into a subspace of a very low dimension, for example two or three, is useful for visualizing multidimensional or higher order data.

The computation of the $V_i$ is accomplished by using the sample covariance matrix $C = X^T X$. The $V_i$ are the eigenvectors of C (an $M \times M$ matrix) that correspond to the N eigenvalues of C. The method for determining the eigenvalues in this manner is known as Singular Value Decomposition (SVD), which is described below.

### 4.3.1 Method of SVD

To determine the principal components of a multi-dimensional signal, PCA uses the method of Singular Value Decomposition. It considers a real $M \times N$ matrix, X of observations which is decomposed as follows;

$$X = USV^T \tag{4.7}$$

Where S is an $M \times N$ non-square matrix with zero entries everywhere, except on the leading diagonal with elements $s_i (= V_{MN}$, M=N) arranged in descending order of magnitude. Each $s_i$ is equal to $\sqrt{\lambda i}$ , the square root of the eigenvalues of $C = X^T X$ [7]. A stem-plot of these values against their index i is known as the singular spectrum or eigenspectrum. The smaller the eigenvalue, the smaller the total energy that is projected along the corresponding eigenvector. Therefore, the smallest eigenvalues are considered to be associated with eigenvectors that describe the noise in the signal. The columns of V form an $N \times N$ matrix of column vectors, which are the eigenvectors of C. The M ×M matrix U is the matrix of projections of X onto the eigenvectors of C. Only the most significant (p largest) eigenvectors are retained by truncating the SVD of X performed. The value of p depends on the nature of the data, but it is taken to be the knee in the Eigen spectrum. $Y = US_pV^T$ gives the truncated SVD and the noise-reduced signals are given by the columns of the M × N matrix Y.

### 4.3.2 Procedure for performing SVD

1 The N non-zero eigenvalues, of the matrix $C = X^T X$ and form a non-square diagonal matrix S by placing the square roots $s_i = \sqrt{\lambda i}$ of the N eigenvalues in descending order of magnitude on the leading diagonal and setting all other elements of S to zero are calculated.

2 The orthogonal eigenvectors of the matrix $C = X^T X$ corresponding to the obtained eigenvalues are calculated, and are arranged in the same order. This ordered collection of column vectors forms the matrix V.

3 The first N column-vectors of the matrix U:$u_i = s_i^{-1} X v_i (i = 1{:}N)$ are calculated

4 The rest of M - N vectors to the matrix U using the Gram-Schmidt orthogonalization process are calculated.

## 4.4 INDEPENDENT COMPONENT ANALYSIS

ICA chooses a measure of independence other than variance which leads to a more effective method for separating signals. The Cocktail Party Problem is a particularly intuitive illustration of the problem of source separation through discovering independent sources, which is the best example to understand ICA.

Blind Source Separation; the Cocktail Party Problem is a classic example of Blind Source Separation (BSS), that separates a set of observations into the constituent underlying (statistically independent) source signals [7]. The Cocktail Party Problem is illustrated in Figure 3.3. Each of the J voices which are heard at a party is recorded by N microphones; a set of N vectors represents the recordings, each of which is a (weighted) linear superposition of the J voices. A J × M matrix, Z denotes as the sources and an N × M matrix, X represents the N recordings, for a discrete set of M samples. By multiplying Z by a N × J mixing matrix, A such that $X^T = AZ^T$ Z transforms it into the observables X. Figure 3.3 illustrates this where sound waves from J =

3 independent speakers ($z_1$, $z_2$, and $z_3$, left) are superimposed (center), and recorded as three mixed source vectors with slightly different phases and volumes at three spatially separated but otherwise identical microphones.

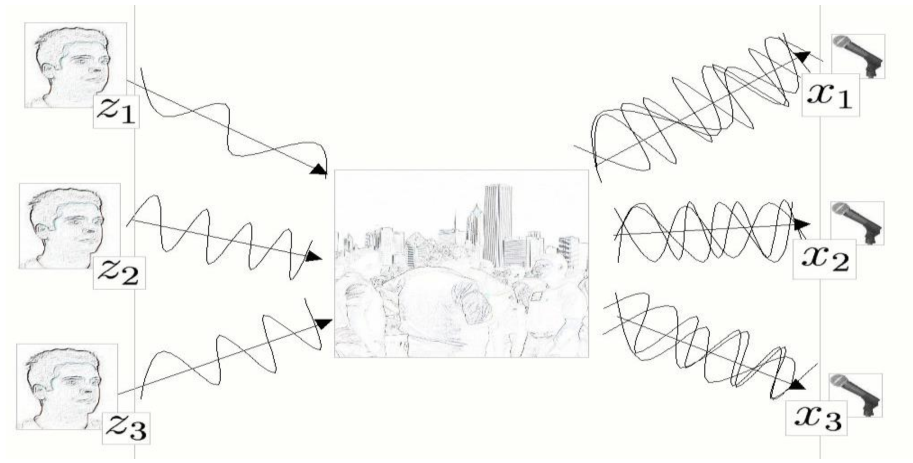


Figure 4.3: The Cocktail Party Problem

Sound waves from J = 3 independent speakers ($z_1$, $z_2$ and $z_3$ left) are superimposed at a cocktail party (center), and are recorded as three mixed source vectors, $x_1$, $x_2$ and $x_3$ on N = 3 microphones (right). The $M \times J$ observations (or recordings), $X^T$ of the underlying sources, $Z^T$, are a linear mixture of the sources, such that $X^T = AZ^T$, where A is a $J \times N$ linear mixing matrix. An estimate $Y^T$, of the $M \times J$ sources $Z^T$, is made by calculating a de-mixing matrix W, which acts on $X^T$ such that $Y^T = WX^T = Z^T$ and $W \approx A^{-1}$.

To recover the original sources from the observed mixture some type of BSS has to be performed, in order to 'pick out' a voice from an ensemble of voices in a crowded room. Mathematically, it is to find a de-mixing matrix W, which when multiplied by the recordings $X^T$, produces an estimate $Y^T$ of the sources $Z^T$. Therefore W is a set of weights (approximately) equal to A. One of the key methods for performing BSS is known as Independent Component Analysis (ICA), where it takes the advantage of (an assumed) linear independence between the sources.

ICA applies the operations to the observed data $X^T$, or the de-mixing matrix, W, and measures the independence between the output signal channels, (the columns of $Y^T$) to derive estimates of the sources, (the columns of $Z^T$). Iterative methods are used to maximize or minimize a given cost function such as mutual information, entropy or the fourth order moment, kurtosis, a measure of non-Gaussianity. The Central Limit Theorem says that the distribution of a sum of independent random variables tends toward a Gaussian distribution. That is, a sum of two independent random variables usually has a distribution that is closer to Gaussian than the two original random variables. In other words, independence is non-Gaussianity. Hence ICA finds a demixing matrix W that maximizes the non-Gaussianity of each source to find independent sources.

In conventional ICA, it never recovers more sources than the number of independent observations ($J \ngtr N$), since this is a form of interpolation and a model of the underlying source signals would have to be used. The essential difference between ICA and PCA is that PCA uses variance, a second order moment, rather than higher order statistics (such as the fourth moment, kurtosis) as a metric to separate the signal from the noise. Independence between the projections onto the eigenvectors of an SVD is imposed by requiring that these basis vectors be orthogonal. ICA forms the subspace which is not necessarily orthogonal and the angles between the axes of projection depend upon the exact nature of the data used to calculate the sources.

SVD imposes orthogonality to the new axes, to de-correlate the data (the projections onto the eigenvectors have zero covariance); it is a much weaker form of independence than that imposed by ICA. Since independence implies uncorrelatedness, many ICA methods constrain the estimation procedure such that it always gives uncorrelated estimates of the independent components, which reduces the number of free parameters, and simplifies the problem.

## RESULTS AND DISCUSSION

All the simulation results using the algorithms discussed above are presented under different subsections, by giving AECG, noise, and other waveforms taken from MIT-BIH database [13] as inputs. The results and discussion are as follows:

## 4.5 AECG WAVEFORM

All the simulation results shown in the later parts are carried out with the following signals as the input to the mentioned methods, which are explained above in this chapter. Figure 4.4 shows the ideal MECG and ideal FECG signals with noise and AECG signal. Their power spectral densities are shown in the Figure 4.5. The AECG signal and noise are used as inputs, whereas the both ideal signals are used for comparison purpose to complete the three techniques, which are explained above (in this chapter).

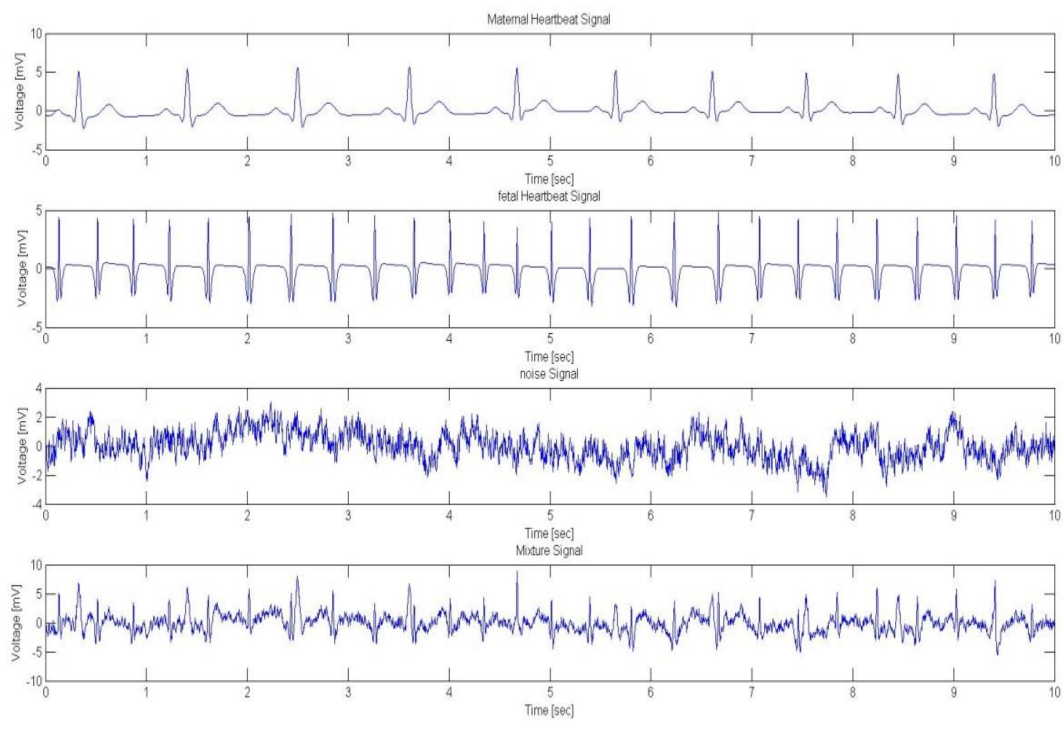


Figure 4.4: MECG, FECG, noise, and AECG waveforms.

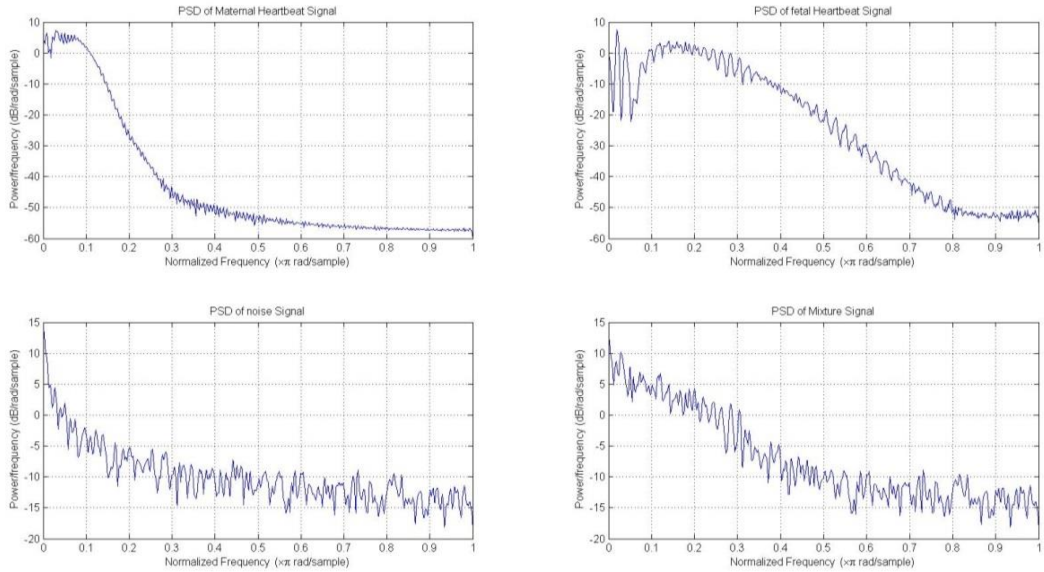


Figure 4.5: PSD of MECG, FECG, noise, and AECG.

## 4.6 RESULTS OF WIENER FILTER

Before applying the wiener filter, the spectral estimation of the signals are required in building the cost function/ transfer function as explained in this chapter under wiener filter section. After the filter is designed, the AECG signal is applied along with the noise estimate signal, whose results are shown in the Figure 4.6.

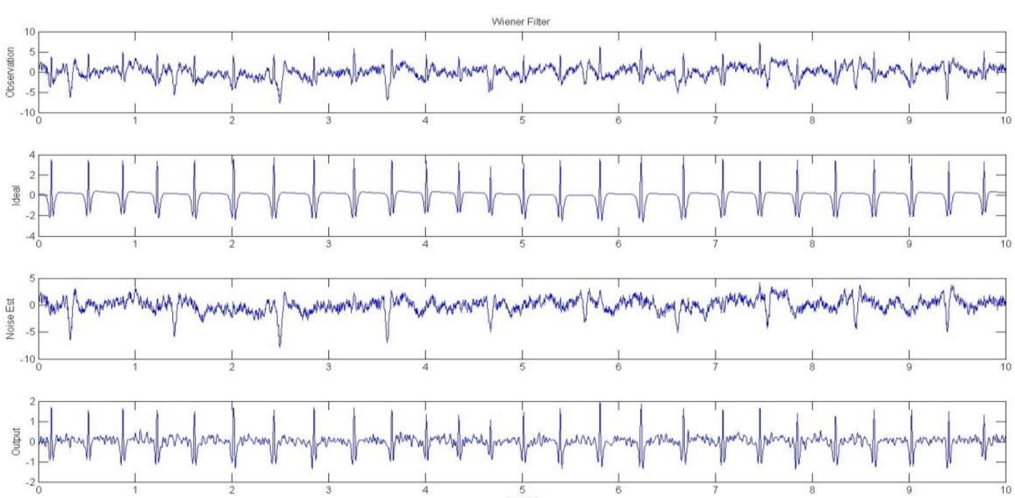


Figure 4.6: Results of wiener filter.

## 4.7 WAVEFORMS FOR BLIND SOURCE SEPARATION

Here spectral estimation of the signals is not required, as the axes on to which the data is projected is not fixed, which are defined by the input data itself (whereas in the wiener filter Fourier components on to which data is projected is fixed) .

The ideal wave forms are show in the figure 4.7, which are used for analysis and comparison purpose. In Figure 4.8 the 3 channel input data is shown which is given as input to the SVD and ICA filters which are defined above.

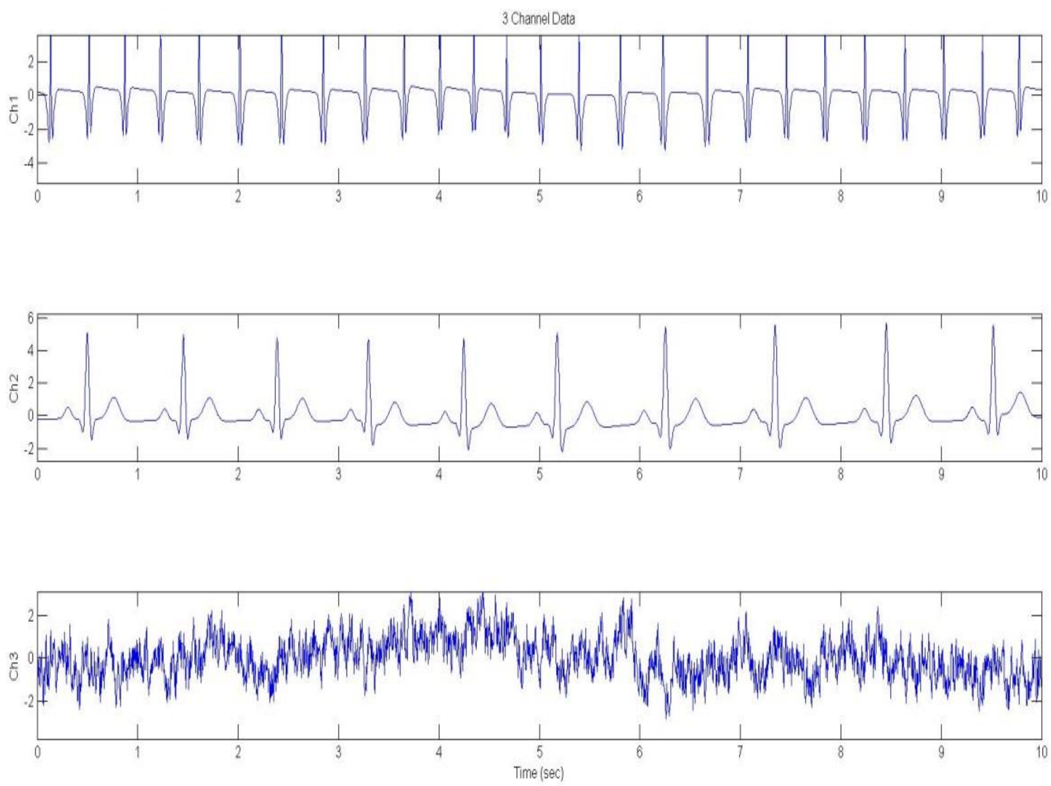


Figure 4.7: Ideal signals of FECG, MECG, and NOISE

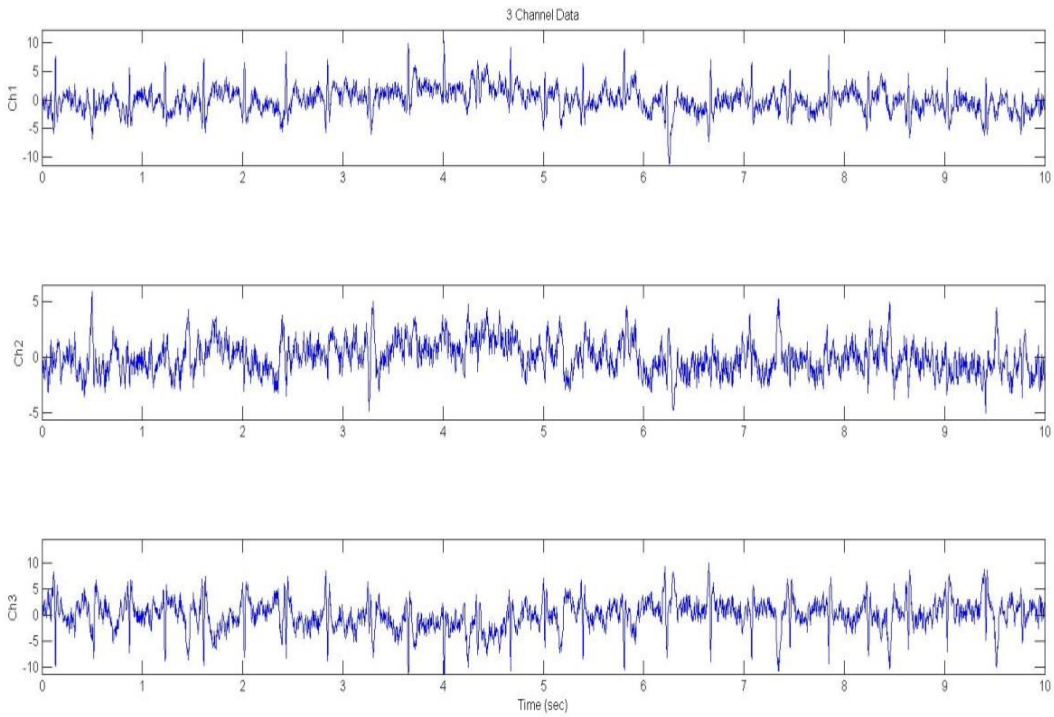


Figure 4.8: 3 channel Input signal to SVD and ICA filters

## 4.8 REULTS OF SVD FILTER

The waveform shown in the Figure 4.8 is given as the input to the SVD filter which projects the data onto the orthogonal axes corresponding to the maximal variance. The data on the new orthogonal axes are shown in the Figure 4.9. Then the required signal may be in any of the channel. From the Figure 4.9 it is clear that the required signal FECG is in the channel 3., selecting that particular channel by making others to zero and retrasformation to the original axes will give the desired ouput. The results are shown in the Figure 4.10.

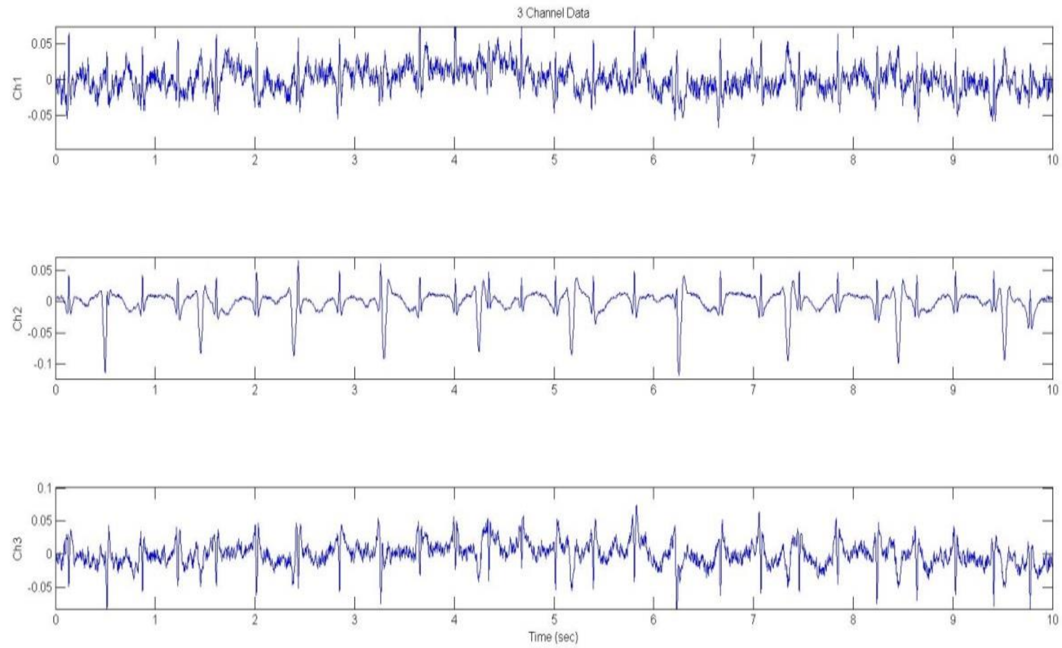


Figure 4.9: Intermediate result of SVD

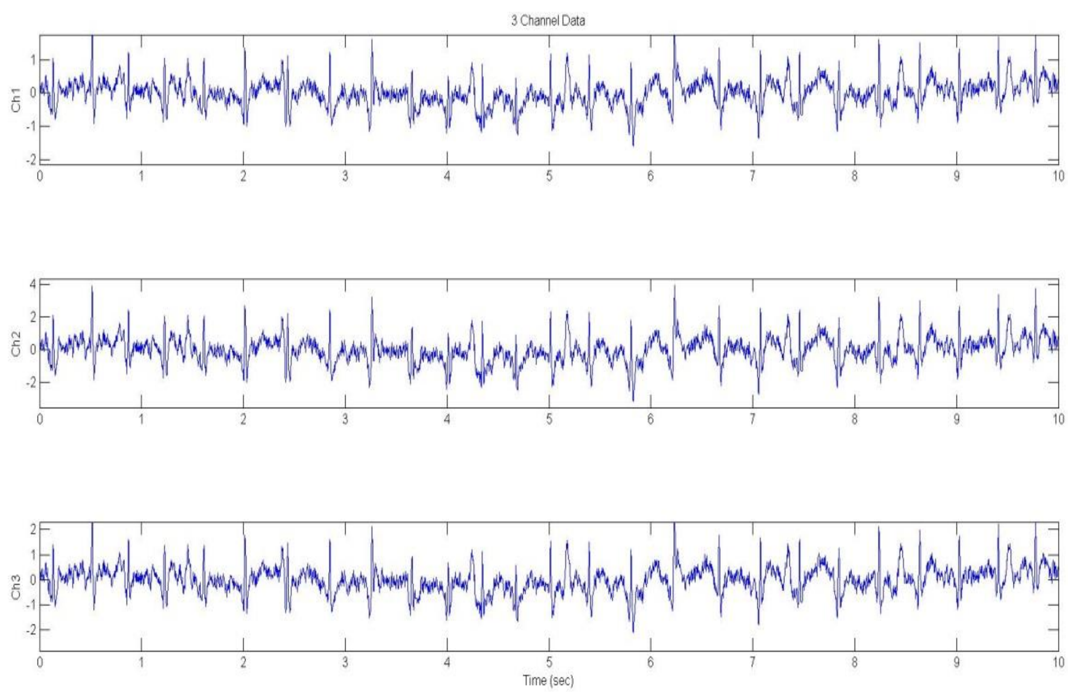


Figure 4.10: Results of SVD.

## 4.9 RESULTS OF ICA FILTER

In the SVD the data is projected onto the orthogonal axes corresponding to maximal variance but the projection does not correspond to the discrete power band in the frequency domain. So, the results are not up to the mark. Whereas in ICA, the data is projected onto the axes (which are not necessarily orthogonal) basing on how much the non-gaussianity of the individual signals.

Similarly after projecting on to the new axes we will get the new data which is shown in Figure 4.11. From the figure the required signal is in the channel 3, similarly we have to select the channel 3 by making others zero which will result in the output/FECG after transforming in to original axes. Results are shown in the Figure 4.12.

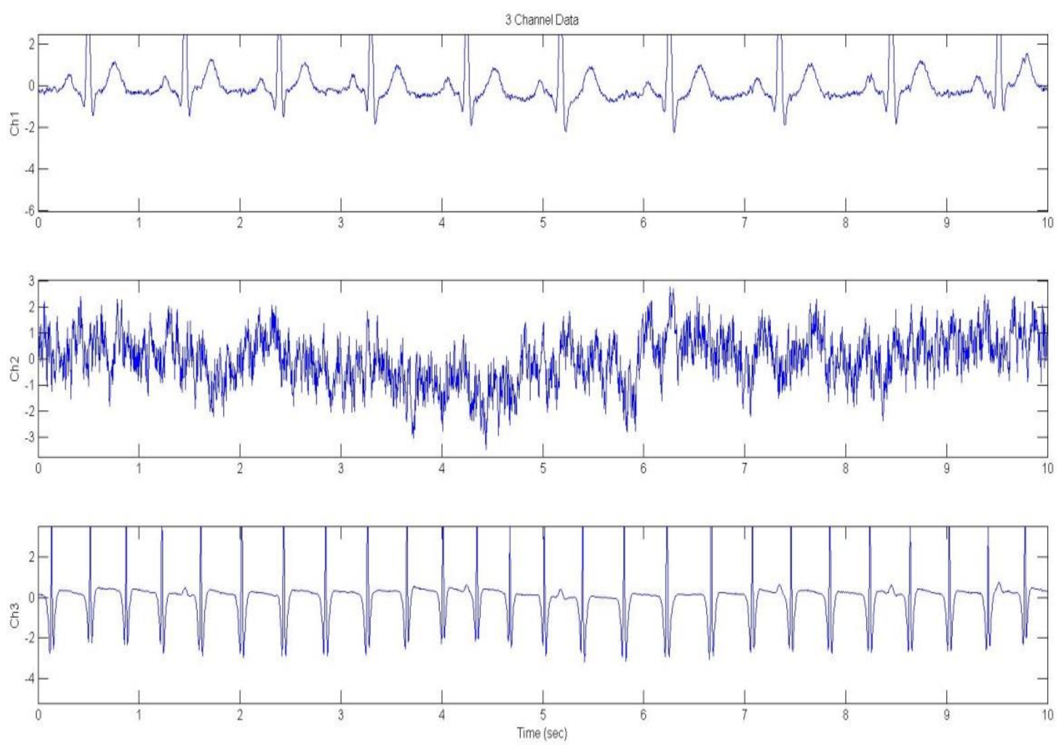


Figure 4.11: Intermediate result of ICA

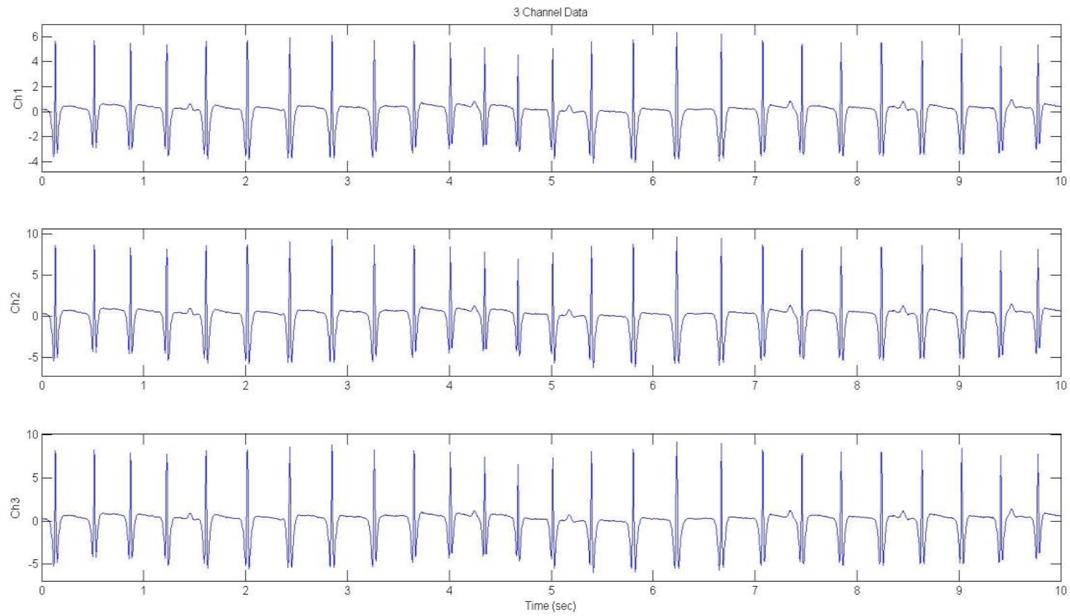


Figure 4.12: Results of ICA.

## 4.10 COMPARISON BASED ON THE OUTPUT WAVEFORMS

From the waveforms it is clearly seen that the ICA is giving the best result of the three and next is the wiener filter. As stated earlier in this section the SVD is giving the poor result.

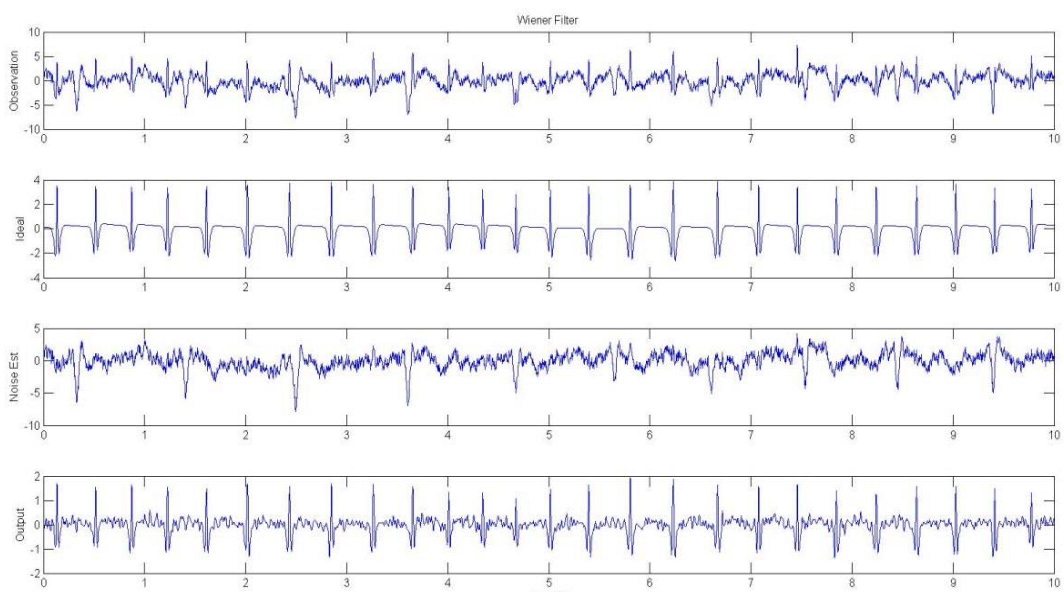


Figure 4.13: Waveforms of the Wiener filter

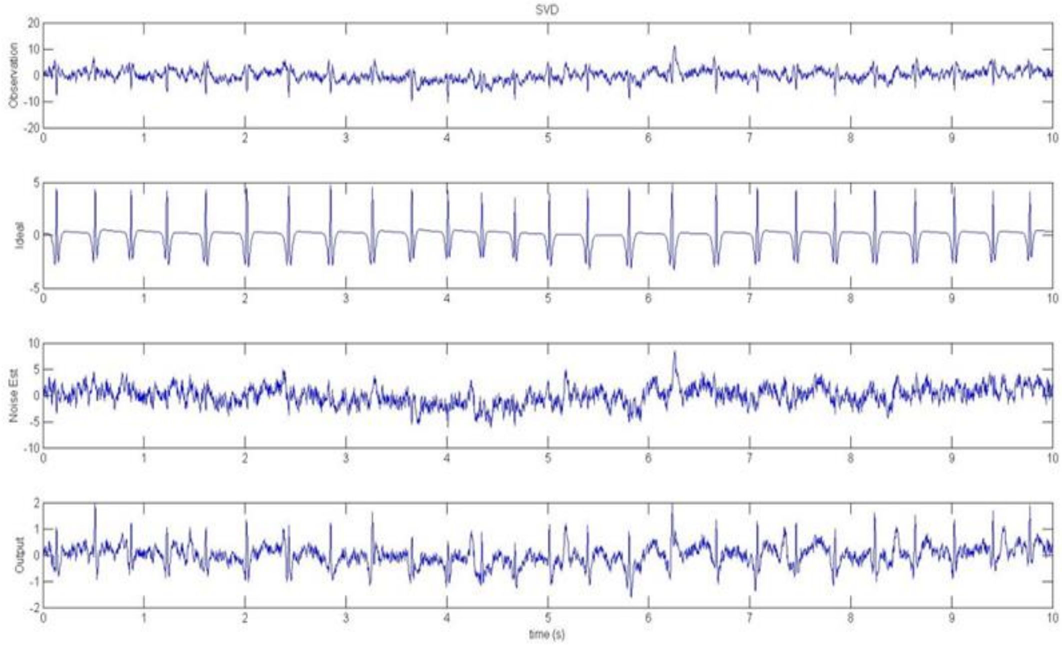


Figure 4.14: Waveforms of the SVD

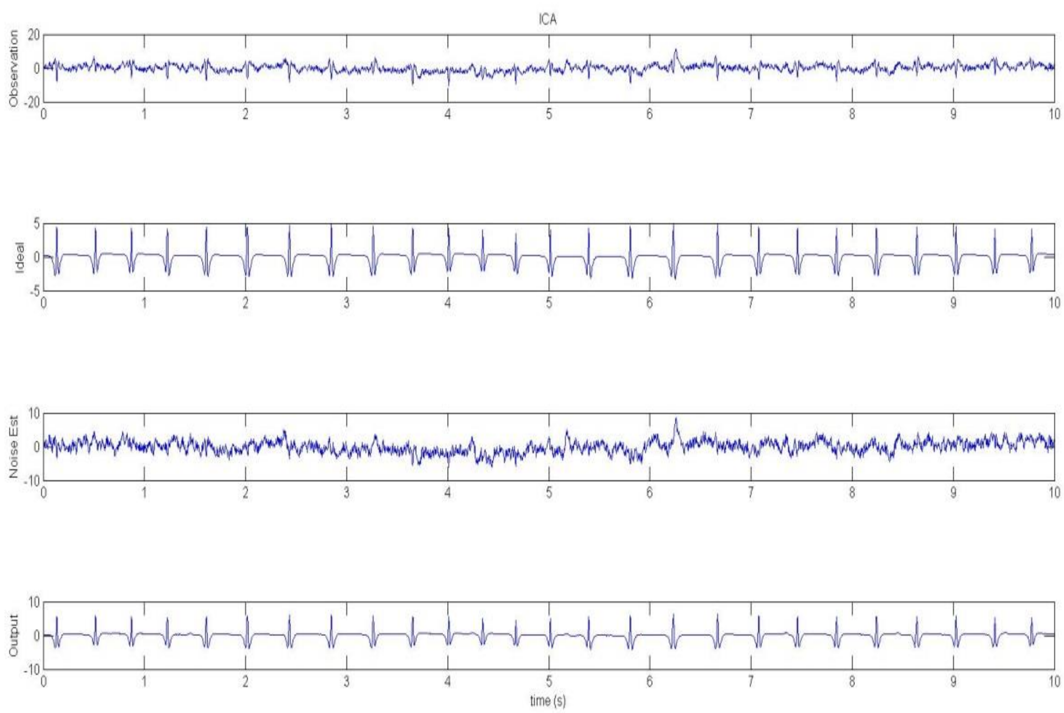


Figure 4.15: Waveforms of the ICA

## 4.11 COMPARISON BASED ON PSDs OF THE RESULTS

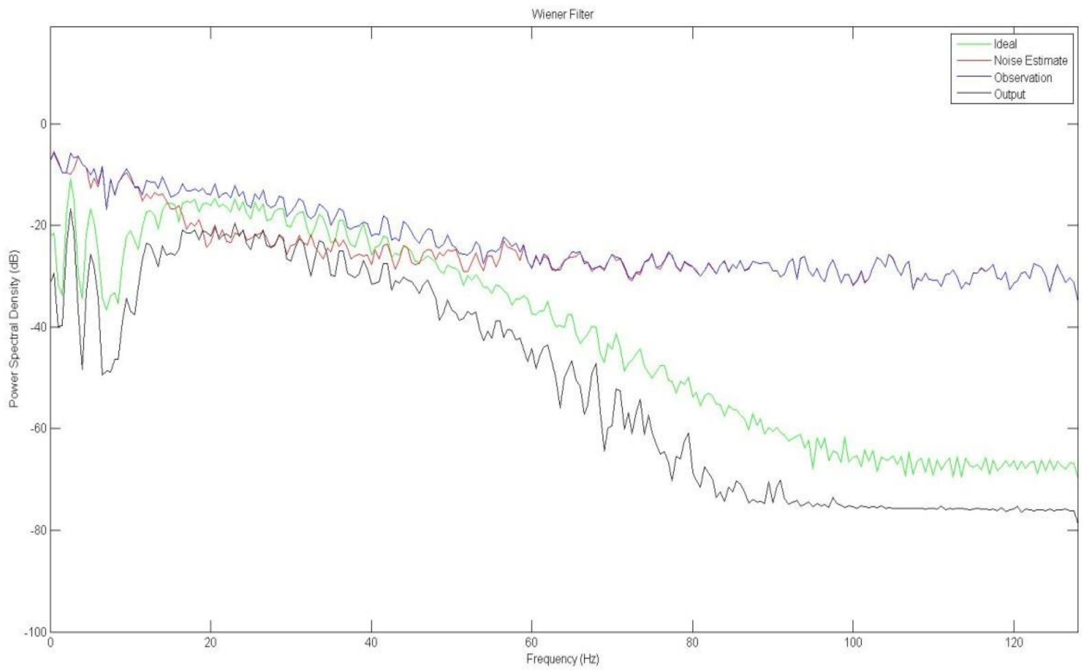


Figure 4.16: PSD of the waveforms of the wiener filter shown in Figure 4.13

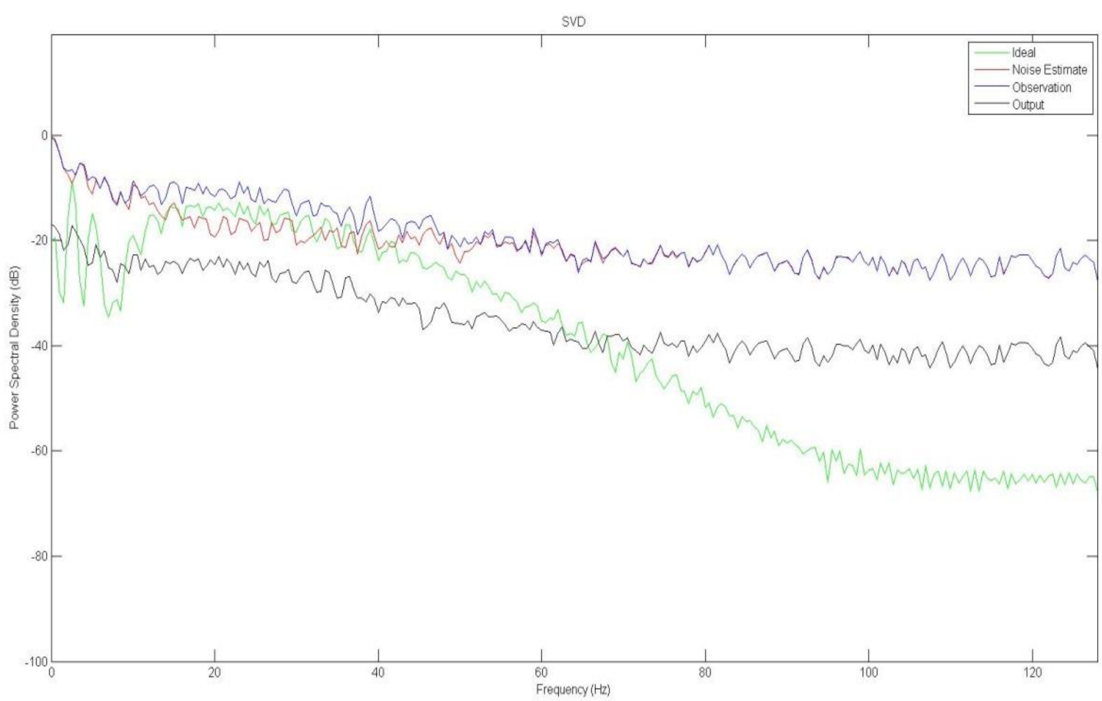


Figure 4.17: PSD of the waveforms of the SVD shown in Figure 4.14

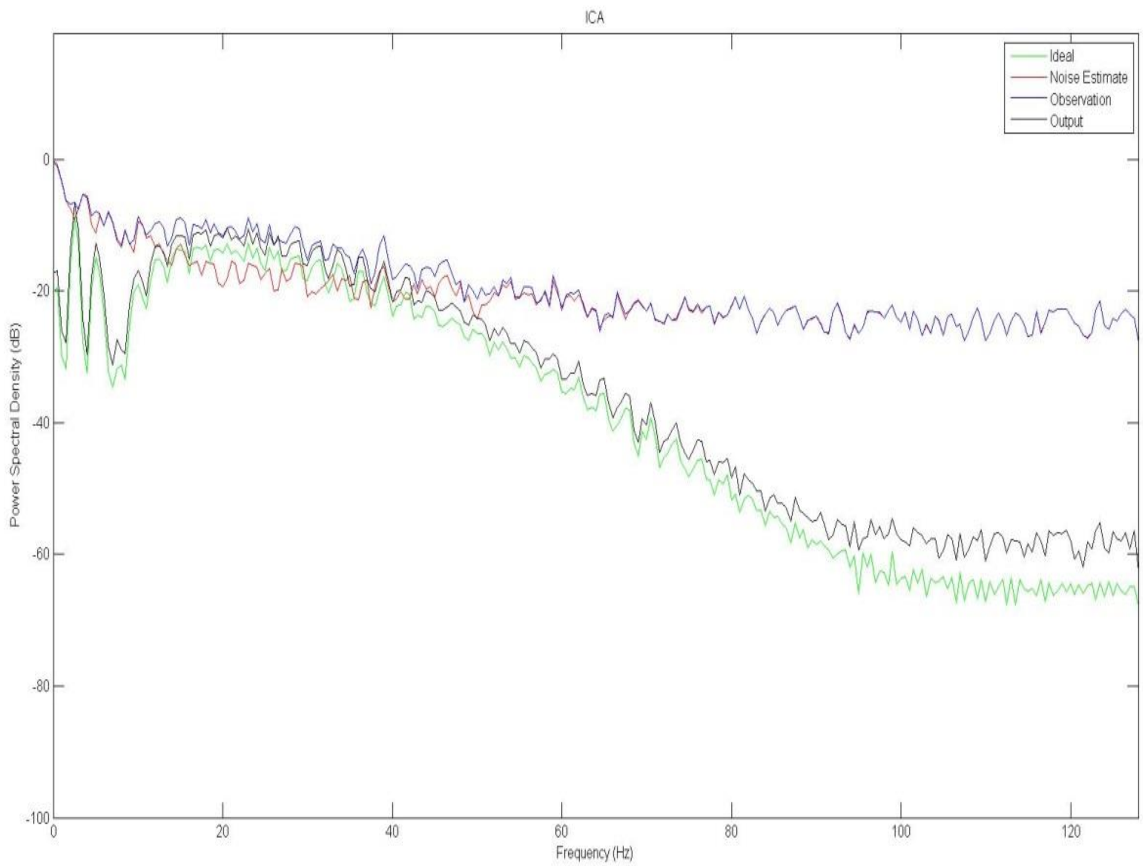


Figure 4.18: PSD of the waveforms of the ICA shown in Figure 4.15

From the PSDs of the results also it is clear that the ICA is standing first, next Wiener filter and then SVD. ICA result is very close to the ideal/desired waveform.

## 4.12 COMPARISON BASED ON THE SNR

The SNRs of the results of the three techniques and the ideal signal are calculated; whose results are shown in the Table I. ICA is having the best and close approximation to ideal waveform. But the Wiener filter and SVD PSDs are not satisfactory. In the above two comparisons Wiener filter is somewhat close to ICA but when it comes to SNR it is close to SVD.

Table I: SNRs of the results of Wiener, SVD and ICA techniques.

| Parameters / Methods | SNR | Ideal_SNR | Abs_diff |
|---|---|---|---|
| SVD | -12.7980 | -6.0073 | 6.7907 |
| Wiener | -10.9838 | -4.7057 | 6.2781 |
| ICA | -3.1313 | -6.0073 | 2.8760 |

Note: Abs_diff = (SNR - Ideal_SNR).

## 4.13 SUMMARY

Wiener filter uses the Fourier domain transformation for filtering purpose, the transfer function is the ratio of power spectrum of desired out to the sum of power spectra of desired output and noise estimation. The power spectrum of the signal is approximated as square of the Fourier transformation stated in the Wiener theorem. The PCA uses the SVD as the tool to transform the data into the new axes which are orthogonal, with variance as the measure which is the weaker form of providing independent components. ICA uses the higher order momentum, kurtosis which is the measure of non-gaussianity to provide the independent components; it is the better method than SVD as the non-gaussianity leads to the independent components according to central limit theorem. AECG signal and other waveforms from the MIT-BIH data base are applied. ICA is showing better performance compared to the other two methods.

# CHAPTER 5

# CONCLUSION AND FUTURE SCOPE

CONCLUSION

FUTURE SCOPE

In this chapter the advantages and disadvantages of all the techniques used for extracting FECG from AECG are discussed. The scope of future work in this domain is also discussed.

## 5.1 CONCLUSION

This thesis throws light on the basics of the FECG, noises effecting the FECG monitoring (non-invasive) and FECG extraction using three different techniques. The thesis begins with the review of some popular work in the field of FECG signal processing and extraction. FECG morphology, FHR monitoring techniques and FECG database are elaborately discussed. Different types of noises that affect the FECG and their origins are also described. For the simulations, the FECG signals and other required signals are taken from the MIT-BIH database. The filtering algorithms used in this thesis are Wiener Filter, SVD (PCA) and ICA techniques. The advantage and limitations of all the used methods are discussed below.

The first algorithm is the non-causal discrete-time Wiener Filter, where the transfer function H(f) is calculated with the $S_y(f)$, the power spectrum of the model of the true signal, y, and $S_d(f)$, the power spectrum estimate of the noise component, d. Where d, noise is the difference between the model of the true signal and observation. The performance of this algorithm is somewhat better than SVD but not better than ICA. As the transfer function is predefined and cannot be varied with the variation in the data, the results are not better than ICA. The output waveform and PSD are at acceptable level, but SNR is poor when compared to ICA (better than SVD).

SVD is the next algorithm used, which decomposes the signal into the components based on the variance as the factor onto a set of orthogonal axes. After decomposing the signal into the different components, the required component is selected by making the other components zero and then retransformed the decomposed components onto the original axes. Thus the FECG is extracted from the AECG using SVD. The SVD has shown the poor performance than the other two as the decomposition does not correspond to a discrete power band in the frequency domain. The output waveform, PSD and the SNR all are poor when compared to the other two algorithms used.

ICA is the last algorithm applied, the transformed axes are based on the non-gaussianity, such as kurtosis (fourth moment). The subspace formed with ICA is not necessarily orthogonal and the angles between the axes of projection depend upon the exact nature of the data used to calculate the sources/desired signal. Hence the results obtained with ICA are better than both the Wiener filter and SVD. The desired waveform FECG is extracted almost exactly with good PSD and SNR value. The limitation of all techniques is that they use multi-channel data, where I used the 3 channel data. More no channels better the result will be.

## 5.2 FUTURE SCOPE

In the present work ICA and SVD are separately used and only 3 channel data is used. Hence the future work can be as follows

- Implementation of SVD to remove the noise and then implementation of ICA for extracting FECG.
- Removing noise with any other regular techniques like adaptive filtering, wavelet technique etc., can be used and later ICA can be performed to extract the FECG from AECG for better result.
- Implementation of the mentioned methods on multi-channel data (more than 3 channels).

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